UNIVERSIDADE DE LISBOA
Instituto de Geografia e Ordenamento do Território
UNIVERSITÉ PARIS 1 PANTHÉON-SORBONNE
École Doctorale de Géographie de Paris

An agent-based approach to model farmers' land use cover change intentions

Eduardo Jonas da Costa Gomes

Orientadores: Prof. Doutor Arnaud Banos
Prof.ª Doutora Patrícia Catarina dos Reis Macedo Abrantes

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Júri:

Presidente: Docteur Pascal Marty, Professeur des universités, Institut de Geographie, Université Paris 1 Panthéon-Sorbonne

Vogais:

- Doctor Elisabete Silva, University Reader, Department of Land Economy, University of Cambridge
- Docteur Thomas Houet, Directeur de research CNRS, LETG-Rennes UMR 6554 CNRS
- Doutor Paulo Morgado, Professor Auxliar, IGOT, Universidade de Lisboa
- Docteur Arnaud Banos, Directeur de research CNRS, Géographie-Cités, Université Paris 1 Panthéon-Sorbonne (orientador)
- Doutora Patrícia Abrantes, Professora Auxiliar, IGOT, Universide de Lisboa (orientadora)

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Keywords

Land-use and land cover change; agricultural land fragmentation; urban growth; farmers' LUCC intentions; driving forces; artificial neural network - multilayer perceptron; Markov chain; cellular automata; agent-based model; scenarios; participatory workshop; stakeholders; spatial planning; land-use strategies.

Acronyms

ABM: Agent-Based Modelling

APA: Agência Portuguesa do Ambiente (The Portuguese Environment Agency)

ANN: Artificial Neural Network

AI: Artificial Intelligence

CA: Cellular Automata

CAP: Common Agricultural Policy

CCDR: Comissão de Coordenação e Desenvolvimento Regional (Regional Coordination and Development Commission)

COS: Carta de Ocupação do Solo (Land cover map)

DGS: Direção-Geral da Saúde (Directorate-General of Health)

DGT: Direcção Geral do Território (Directorate-General for Territorial Development)

EC: European Commission

EEA: European Environment Agency

FAO: Food and Agriculture Organization

FARMER: FARmers intentions of changing land use in MEtropolitan Regions

GIS: Geographic Information Systems

GSDSS: Group Spatial Decision Support Systems

ICNF: Instituto da Conservação da Natureza e das Florestas (Institute for Nature Conservation and Forestry)

IPCC: Intergovernmental Panel on Climate Change

KIA: Kappa Index of Agreement

LAND: Land-use chAnge and Neighbouring Distance

LBGPPSOTU: Lei de Bases Gerais da Política Pública de Solos de Ordenamento do território e de Urbanismo (Portuguese Framework Law for the Policy on Territorial Management and Urbanism)

LUC: Land Use/ Cover

LUCC: Land Use and Cover Change

Markov: Markov Chain Model

MLP: Multilayer Perceptron

PDM: Plano Diretor Municipal (Municipal Master Plan)

OECD: Organisation for Economic Co-operation and Development

PEOT: Planos Especiais de Ordenamento do Território (Special Plans for Spatial Planning)

PIOT: Planos Intermunicipais de Ordenamento do Território (Inter-municipal spatial plan)

PNPOT: Programa Nacional da Política de Ordenamento do Território (National Program for the Territorial Management Policy)

PROT: Programa Regional de Ordenamento do Território (Regional Development Model)

PS: Plano Sectorial (Sectoral Plan)

RAN: Reserva Agrícola Nacional (National Agricultural Reserve)

REN: Reserva Ecológica Nacional (National Ecological Reserve)

SDSS: Spatial Decision Support Systems

VIF: Variance Inflation Factor

UN: United Nations

UNESCO: The United Nations Educational, Scientific and Cultural Organization

WB: The World Bank

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This document is gathered as a manuscript-based thesis.

Chapter five is an adapted version of the following published papers:

Gomes, Eduardo, Banos, Arnaud, Abrantes, Patrícia, Rocha, Jorge (2018). Assessing the Effect of Spatial Proximity on Urban Growth. Sustainability. 10: 1308.

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Abstract

Land Use and Cover Change (LUCC) occurs as a consequence of both natural and human activities, causing impacts on biophysical and agricultural resources. In enlarged urban regions, the major changes are those that occur from agriculture to urban uses. Urban uses compete with rural ones due among others, to population growth and housing demand. This competition and the rapid nature of change can lead to fragmented and scattered land use development generating new challenges, for example, concerning food security, soil and biodiversity preservation, among others.

Landowners play a key role in LUCC. In peri-urban contexts, three interrelated key actors are pre-eminent in LUCC complex process: 1) investors or developers, who are waiting to take advantage of urban development to obtain the highest profit margin. They rely on population growth, housing demand and spatial planning strategies; 2) farmers, who are affected by urban development and intend to capitalise on their investment, or farmers who own property for amenity and lifestyle values; 3) and at a broader scale, land use planners/ decision-makers.

Farmers' participation in the real estate market as buyers, sellers or developers and in the land renting market has major implications for LUCC because they have the capacity for financial investment and to control future agricultural land use.

Several studies have analysed farmer decision-making processes in peri-urban regions. These studies identified agricultural areas as the most vulnerable to changes, and where farmers are presented with the choice of maintaining their agricultural activities and maximising the production potential of their crops or selling their farmland to land investors. Also, some evaluate the behavioural response of peri-urban farmers to urban development, and income from agricultural production, agritourism, and off-farm employment. Uncertainty about future land profits is a major motivator for decisions to transform farmland into urban development. Thus, LUCC occurs when the value of expected urban development rents exceeds the value of agricultural ones. Some studies have considered two main approaches in analysing farmer decisions: how drivers influence farmer's decisions; and how their decisions influence LUCC.

To analyse farmers' decisions is to acknowledge the present and future trends and their potential spatial impacts. Simulation models, using cellular automata (CA), artificial neural networks (ANN) or agent-based systems (ABM) are commonly used.

This PhD research aims to propose a model to understand the agricultural land-use change in a peri-urban context. We seek to understand how human drivers (e.g., demographic, economic, planning) and biophysical drivers can affect farmer's intentions regarding the future agricultural land and model those intentions. This study presents an exploratory analysis aimed at understanding the complex dynamics of LUCC based on farmers' intentions when they are faced with four scenarios with the time horizon of 2025: the A0 scenario – based on current demographic, social and economic trends and investigating what happens if conditions are maintained (BAU); the A1 scenario – based on a regional food security; the A2 scenario – based on climate change; and the B0 scenario – based on farming under urban pressure, and investigating what happens if people start to move to rural areas. These scenarios were selected because of the early urbanisation of the study area, as a consequence of economic, social and demographic development; and because of the interest in preserving and maintaining agriculture as an essential resource. Also, Torres Vedras represents one of the leading suppliers of agricultural goods (mainly fresh fruits, vegetables, and wine) in Portugal.

To model LUCC a CA-Markov, an ANN-multilayer perceptron, and an ABM approach were applied. Our results suggest that significant LUCC will occur depending on farmers' intentions in different scenarios. The highlights are: (1) the highest growth in permanently irrigated land in the A1 scenario; (2) the most significant drop in non-irrigated arable land, and the highest growth in the forest and semi-natural areas in the A2 scenario; and (3) the greatest urban growth was recognised in the B0 scenario. To verify if the fitting simulations performed well, statistical analysis to measure agreement and quantity-allocation disagreements and a participatory workshop with local stakeholders to validate the achieved results were applied. These outcomes could provide decision-makers with the capacity to observe different possible futures in 'what if' scenarios, allowing them to anticipate future uncertainties, and consequently allowing them the possibility to choose the more desirable future.

Résumé

Les changements d'usage et occupation des sols résultent d'activités naturelles et anthropiques et peuvent avoir un impact négatif sur les ressources naturelles et même agricoles. Dans les régions métropolitaines, les principaux changements d'usage des sols sont ceux qui proviennent de la transformation des terres agricoles en des couvertures artificielles, essentiellement pour des usages urbains, industriels, de transports et de loisirs. Ces usages sont en concurrence avec les utilisations agricoles en raison, surtout, de la croissance démographique et de la recherche de nouvelles aires de construction. Cette concurrence permanente et la rapidité dont elle se produit a contribué largement à fragmentation et la dispersion à la fois des terres agricoles et des usages artificiels. Ces changements posent de défis, en particulier dans les domaines de la sécurité alimentaire, mais aussi de la nécessité de préserver les sols et la biodiversité dans des contextes plus urbanisés.

Les propriétaires fonciers jouent un rôle majeur en ce qui concerne les changements d'occupation des sols. Dans un contexte périurbain, trois acteurs clefs sont généralement identifiés dans le processus de décision de changement d'utilisation ou la couverture des sols : 1) Les investisseurs ou les promoteurs immobiliers, qui souhaitent obtenir un rendement maximal dans un contexte de développement urbain, en essayant d'obtenir la marge de profit la plus élevée possible. Leurs décisions dépendent souvent de la croissance démographique, de la recherche de nouveaux logements et des stratégies de planification et d'organisation du territoire ; 2) les agriculteurs qui sont affectés par les attentes concernant le développement urbain et qui prétendent capitaliser leurs investissements, ou les agriculteurs qui prétendent maintenir leurs terrains pour une question de consommation personnelle, agrément et/ou style de vie ; 3) à une échelle plus large, les acteurs qui planifient et définissent des stratégies pour l'usage futur de l'occupation du sol.

La participation des agriculteurs au marché immobilier en tant qu'acheteurs, vendeurs ou agents sur le marché de la location présente des implications majeures sur l'évolution de l'utilisation et de l'occupation des sols, dans la mesure où ils ont la capacité d'investir financièrement, et en même temps, de contrôler l'usage futur de l'utilisation agricole.

Plusieurs études ont analysé les processus de prise de décision des agriculteurs dans les régions périurbaines. Ces études ont identifié les aires agricoles comme étant les aires les plus

vulnérables aux changements, et où les agriculteurs ont la possibilité de maintenir leur activité agricole et de maximiser le potentiel de production agricole ou de vendre leurs terres agricoles à des investisseurs. D'autres études ont évalué la réponse comportementale des agriculteurs périurbains en fonction du développement urbain, du rendement de la production agricole, de l'agrotourisme et de l'emploi non directement lié à l'activité agricole. L'incertitude sur le revenu futur que les agriculteurs peuvent tirer de leur activité agricole est souvent un facteur décisif dans conversion des terres agricoles en aire urbaine. En ce sens, des changements dans l'utilisation et l'occupation des sols peuvent se produire lorsque le revenu provenant de la vente d'une terre agricole en faveur du développement urbain dépasse le revenu pouvant provenir de la production agricole.

L'analyse des intentions des agriculteurs selon différents scénarios est extrêmement pertinente dans la mesure où elle permet de connaître les impacts potentiels résultant des modifications apportées à l'utilisation et à l'occupation des sols. La présente thèse vise à analyser les intentions des agriculteurs en ce qui concerne les changements d'utilisation et d'occupation du sol dans un contexte périurbain. L'objectif est d'identifier comment les forces motrices associées aux facteurs anthropiques (notamment dans les domaines économique, social et de planification) et biophysiques peuvent affecter les intentions des agriculteurs concernant l'utilisation future des terres agricoles. Cette étude propose une analyse exploratoire visant à comprendre la complexité associée à la dynamique de l'utilisation des sols et aux changements d'affectation des terres, en fonction des intentions des agriculteurs. Ces intentions ont été obtenues à partir d'entretiens avec des agriculteurs, confrontés à quatre scénarios pour l'horizon 2025. Il s'agit du scénario A0, qui repose sur le maintien de la tendance socio-économique actuelle ; du scénario A1 - basé sur chaînes d'approvisionnement alimentaire courtes ; du scénario A2 - basé sur une réchauffement climatique ; et enfin du scénario B0 - qui est lié à une demande croissante de terrains à bâtir pour créer de nouvelles aires résidentielles et/ou touristiques.

L'identification et la sélection de ces scénarios ont été basées sur les caractéristiques spécifiques de la zone d'étude, qui est la municipalité de Torres Vedras (Portugal). Cette municipalité, en pleine zone littorale a été témoin d'une rapide urbanisation, principalement durant les années 1990 et au début des années 2000. Son développement économique et social a bénéficié de la proximité et d'une amélioration des accessibilités à la capitale Lisbonne ce qui a entraîné une réduction des surfaces agricoles ainsi que leur fragmentation. Mais, en contraste la municipalité de Torres Vedras est l’un des principaux fournisseurs de produits agricoles (fruits, légumes et vin) au Portugal, en particulier pour la région métropolitaine de Lisbonne. Ces raisons font que Torres Vedras soit un cas étude intéressant où la portée économique, sociale et urbaine se creuse avec la préservation et le maintien de l’activité agricole.

Il existe actuellement un large éventail de modèles complexes permettant de modéliser et de simuler les modifications futures de l’usage et de l’occupation des sols. Les automates cellulaires, les réseaux de neurones artificiels et les systèmes basés sur des agents sont ceux qui ont été le plus récemment utilisés dans la littérature. Dans cette thèse, les intentions de changement de l'usage et de l'occupation du sol par les agriculteurs et pour des différents scénarios ont été associées à différentes forces motrices et projetées spatialement à l'aide des différents modèles : les automates cellulaires (chaînes de Markov), les réseaux de neurones artificiels (perceptron multicouche), et les cas des modèles à base d’agents.

Les résultats identifiés, à travers les différents modèles, suggèrent que des changements significatifs dans l'utilisation et l'occupation des sols vont se produire en fonction des intentions des agriculteurs dans les différents scénarios. On a pu identifier en particulier (1) une croissance des cultures irriguées de manière permanente dans le scénario A1; (2) une diminution des terres agricoles non irriguées et une croissance des zones forestières et semi-naturelles dans le scénario A2; et (3) une croissance des zones artificialisées dans le scénario B0.

Afin de contrôler les performances de la modélisation des changements d’usage et d’occupation du sol pour les prévisions futures, différentes techniques d’étalonnage et de validation ont été utilisées pour évaluer d'une part la concordance entre les cellules prévues et attendues, et d'autre part l’affectation et la quantité de cellules dans chacune des classes d'utilisation et d'occupation du sol. Par ailleurs aux différentes techniques statistiques utilisées dans la validation des modèles (par exemple, indice de Kappa, kLocation, KHistogramme, valeur V de Cramer et métriques de paysage), un atelier participatif a été organisé avec des agents du territoire de la commune de Torres Vedras liés à l'aménagement du territoire, à l'agriculture, aux forêts et au développement immobilier. La réalisation de cet atelier a permis de valider les résultats obtenus par les différents modèles, ainsi que d'identifier des stratégies à mener pour chacun des scénarios.

Les résultats obtenus dans le cadre de cette thèse devraient permettre aux décideurs d'observer différents futurs possibles dans des scénarios de type "et si", leur permettant ainsi d'anticiper les incertitudes futures et, par conséquent, de choisir l'avenir le plus désirable en matière de l'usage et de l'occupation des sols.

Resumo

As alterações de uso e ocupação do solo ocorrem em consequência das atividades naturais e antrópicas, causando impactos negativos nos recursos biofísicos e agrícolas. Nas regiões metropolitanas, as principais alterações de uso e ocupação do solo são as que ocorrem da alteração do uso de solo agrícola para usos artificiais. Estes usos competem com o uso agrícola devido, essencialmente, ao crescimento populacional e à procura por novas áreas para construção. Esta permanente competição e a forma rápida como ela muitas vezes ocorre, tem levado a uma crescente fragmentação e dispersão tanto do uso do solo agrícola como do uso do solo artificial. Estas alterações produzem novos desafios nomeadamente nas questões da segurança alimentar, e na premência da preservação do solo e da biodiversidade.

Os proprietários de terrenos desempenham um papel fundamental nas alterações de uso e ocupação do solo. Num contexto periurbano, são geralmente identificados três atores chave no processo de decisão de alteração de uso e ocupação do solo, nomeadamente: 1) investidores ou promotores imobiliários, que esperam obter o máximo rendimento num contexto de desenvolvimento urbano, tentando obter a maior margem de lucro possível. As suas decisões estão muitas vezes dependentes do crescimento populacional, da procura por novas habitações e das estratégias de planeamento e ordenamento do território; outros importantes atores num contexto periurbano são 2) os agricultores que são afetados pela expectativa de desenvolvimento urbano e pretendem capitalizar os seus investimentos, ou os agricultores que pretendem manter os seus terrenos agrícolas por uma questão de auto consumo, amenidade, e/ou estilo de vida; e 3) numa escala mais alargada encontram-se os atores decisores do planeamento nas questões de definição de estratégias para o futuro uso de ocupação do solo.

A participação dos agricultores no mercado imobiliário enquanto compradores, vendedores ou como agentes no mercado do arrendamento de terrenos agrícolas apresenta grandes implicações para as alterações de uso e ocupação do solo, na medida em que estes possuem a capacidade de investimento financeiro, e ao mesmo tempo, de controlo sobre o uso futuro da utilização agrícola.

Diversos estudos têm analisado os processos de tomada de decisão dos agricultores nas regiões periurbanas. Estes estudos têm identificado as áreas agrícolas como as mais

vulneráveis de alteração, onde os agricultores têm a opção de manter a sua atividade agrícola e maximizar o potencial de produção das suas culturas ou vender os seus terrenos agrícolas para investidores. Outros estudos têm avaliado a resposta comportamental dos agricultores periurbanos em relação ao desenvolvimento urbano, ao rendimento da produção agrícola, ao agroturismo, e ao emprego não diretamente ligado à atividade agrícola. A incerteza sobre o rendimento futuro que os agricultores podem obter a partir da atividade agrícola é, muitas vezes, um fator decisivo nas decisões de converter terrenos agrícolas para desenvolvimento urbano. Neste sentido, as alterações de uso e ocupação do solo podem ocorrer quando o rendimento da venda de um terreno agrícola para desenvolvimento urbano é superior ao rendimento que pode ser extraído pela produção agrícola.

Analisar as intenções dos agricultores, relativamente às alterações de uso e ocupação do solo tendo por base diferentes cenários, é de extrema relevância na medida em que permite reconhecer potenciais impactos. O presente projeto de doutoramento tem como objetivo analisar as intenções dos agricultores nas questões de alteração de uso e ocupação do solo num contexto periurbano. Pretende-se identificar de que modo as forças motrizes ligadas aos fatores antrópicos (nomeadamente nas questões demográficas, sociais, económicas e de planeamento) e a fatores biofísicos, podem afetar as intenções dos agricultores em relação à utilização futura do uso do solo agrícola.

Este estudo apresenta uma análise exploratória que visa compreender a complexidade associada à dinâmica das alterações de uso e ocupação do solo, tendo por base as intenções dos agricultores. Estas foram obtidas a partir da realização de entrevistas a agricultores, quando confrontados perante quatro cenários para o horizonte temporal de 2025. Sendo eles: o cenário A0 – que tem por base a manutenção da atual tendência demográfica, social e económica; o cenário A1 – que é baseado na promoção de cadeias curtas de abastecimento alimentar (segurança alimentar a nível regional); o cenário A2 – baseado num aquecimento climático (verificando-se o aumento de períodos de seca); e por fim o cenário B0 – está relacionado com uma crescente procura por terrenos para construção, e por uma procura crescente por novas áreas residenciais ou para fins turísticos.

A identificação e seleção destes cenários tiveram igualmente por base as características específicas do caso de estudo selecionado, o concelho de Torres Vedras (Portugal). Neste concelho verificou-se uma rápida urbanização principalmente durante a década de 1990 e início da década de 2000, em resultado do desenvolvimento económico e social verificado na região, tendo levado a uma diminuição das áreas agrícolas assim como a um aumento da sua fragmentação. Para além deste fator a escolha do concelho de Torres Vedras teve por base a importância da preservação e manutenção da atividade agrícola no concelho, pela sua relevância tanto económica como social. O concelho de Torres Vedras é um dos principais fornecedores de produtos agrícolas em Portugal, com destaque para a região metropolitana de Lisboa, nomeadamente de fruta, produtos hortícolas e vinho.

Atualmente existe um conjunto alargado de modelos complexos que permitem a modelação e a simulação futura das alterações de uso e ocupação do solo. Os mais utilizados recentemente na literatura têm sido os autómatos celulares, as redes neuronais artificiais e os sistemas baseados em agentes. Neste projeto de doutoramento acoplando as intenções de alteração de uso e ocupação do solo dos agricultores para os diferentes cenários, e utilizando os modelos acima mencionados foram projetadas espacialmente as referidas intenções, conjuntamente com diferentes forças motrizes, e assim verificadas as alterações de uso e ocupação do solo para os diferentes cenários e modelos. Especificamente, no caso dos autómatos celulares foram utilizadas cadeias de Markov, para as redes neuronais artificiais foi utilizada uma perceptron multicamada para a análise do crescimento das áreas artificializadas, e por fim no caso dos modelos baseados em agentes foram acopladas as intenções dos agricultores.

Os resultados identificados, através dos diferentes modelos, sugerem que significativas alterações de uso e ocupação do solo ocorrerão tendo por base as intenções dos agricultores nos diferentes cenários. Como maiores destaques identificam-se (1) o maior crescimento das culturas permanentemente irrigadas no cenário A1; (2) um decréscimo dos terrenos agrícolas não irrigados, e o maior crescimento das áreas florestais e semi-naturais no cenário A2; e (3) o maior crescimento de áreas artificializadas no cenário B0.

No sentido de verificar se a modelação das alterações de uso e ocupação do solo detinham um bom desempenho na predição futura, diferentes técnicas de calibração e validação foram utilizadas, tanto para avaliar a concordância entre células preditas e esperadas, como na alocação e quantidade de células em cada uma das classes de uso e ocupação do solo. Para além das diferentes técnicas estatísticas utilizadas na validação dos modelos (por exemplo, índice Kappa, kLocation, KHistogram, Cramer´s V value, e métricas da paisagem), foi realizado um workshop participativo com agentes do território do concelho de Torres Vedras com ligações ao planeamento do uso do solo, à agricultura, às florestas e à promoção imobiliária. A realização deste workshop permitiu validar os resultados obtidos nos diferentes modelos, assim como na identificação de estratégias para cada um dos cenários.

Os resultados obtidos neste projeto de doutoramento deverão permitir aos decisores do planeamento do uso e ocupação do solo a capacidade de observar diferentes futuros possíveis em cenários "e se", permitindo-lhes antecipar futuras incertezas e, consequentemente, permitindo-lhes escolher o futuro mais desejável.

General Introduction

Human activities have been recognised as the dominant force that have been influenced the LUCC globally (Bucała, 2014), affecting natural ecosystems (Pham et al., 2015) and the physical structure of the landscape. Worldwide, about 55 per cent of the population live in urban areas, in Europe about 74% (UN, 2018), and in Portugal around 64% in 2018 (WB, 2019).

In Portugal, human activities have been also identified as the main driver. Improvements in road accessibility since joining the European community in 1986, the widespread use of motor vehicles associated with an increasing economy, have contributed to intensifying urbanisation (Abrantes et al., 2016; Gaspar, 2003; Marques da Costa and Marques da Costa, 2003), occurred mainly along the coast, particularly in both Lisbon and in Porto metropolitan regions. High levels of urbanisation have been transformed the natural land into artificial surfaces (Abrantes et al., 2013), mainly to residential and touristic activities (EEA, 2007), registering an increase of 31% of artificial surfaces between 1995 and 2010 (data source: DGT (2010, 1995)).

These conversions have negative impacts to the prime agricultural land (Verheye, 2009), and they are one of the main spatial planning challenges in Europe (EEA, 2013; EEA, 2006). The landscape is changing. LUCC have critical implications in the disappearance of natural and agricultural areas, and is one of the most visible impacts on the environmental system (Liu et al., 2007; Salvati and Carlucci, 2014), leading to irreversible damages in natural resources.

This phenomena is more critical in peri-urban regions of western urbanised countries, where some consequences have been recognized, such as the farmland fragmentation increase; rising traffic congestion (Chen and Chang, 2014); the disappearance of wildlife populations, species, and habitats (Jaeger and Madrinan, 2011); as well as direct consequences for food supply and foodshed basin (Gutzler et al., 2015; Satterthwaite et al., 2010).

These changes are often related to land agents' decisions, in which they are driven by different interests. They can be recognized as speculators or developers (Bhatta, 2010; Brown et al., 1981); farmers, interested to invest in their agricultural production (Ettema et al., 2007; van Vliet et al., 2015); as well as farmers, who have interested in the amenity qualities of the peri-urban regions (Paül and McKenzie, 2013; Valbuena et al., 2010b). Analyse who they are, as well as understand what are their interests is critical to better manage the land (Capozza and Helsley, 1990; Heimlich and Anderson, 2001).

Different drivers influence land-use decision-making and can determine agricultural profitability and land valuation. Farmer decisions on whether to convert farmland to urban land or to preserve it are two key issues. Some key drivers can help to maintain farming activity such as the proximity to agricultural cooperatives, commercial markets, and large consumers demand; as well as agricultural subsidies (i.e. at European Union level) such as the rural development or the Common Agricultural Policy (CAP) which aim to implement agricultural innovation mainly through the organisation of the food chain, and climate-resilient economies. However, other key drivers can both contribute to preserve farming activity or to put agricultural land under urban pressure such as the proximity to the transport network, which acts as both preserving/ converting land. On the one hand, it facilitates the distribution of agricultural production, on the other hand, it enables urban growth and urban population housing demand closer to rural amenities; land price as a valuable index in decisions about whether or not to rent, buy, sell or develop. The distance to the city centre also influences urban and agricultural land prices and rents; and land use planning instruments (Chicoine, 1981; Dawkins and Nelson, 2002; Plantinga et al., 2002). Planning instruments can constraint or guide development through the use of land restrictions and land strategies. In Portugal, the regulatory land planning framework is implemented at the municipal level, through Municipal Master Plans (PDM) regulating urban development, land use classifications, and land-use constraints such as the National Agricultural Reserve (RAN) that identifies, monitors, and protects the best agricultural soils. RAN derives from national law and then is applied, and its limits are defined at the municipal level.

Despite the existence of these policies, farmland conversion into urban uses continues, because they are poorly safeguarded at the local planning level (Abrantes et al., 2016; Marques da Costa et al., 2011). Measures such as urban containment policies, regulate agricultural fragmentation and preserve natural and agricultural areas are some of the policies that can be considered to mitigate agricultural land conversion to other uses. Understand the key trends in LUCC is critical to promote policies to improve the lives of both urban and rural inhabitants, by promoting a sustainable environment.

To address this problematic, complexity science can provide an interesting theoretical and methodological approach to identify these LUCC conversions, recognising how farmers' decisions influence agricultural land use dynamics. Complex spatial models can be useful to couple agents behaviours with more spatial static data, i.e. to integrate farmer's LUCC intentions in its rules and spatially project future LUCC, identifying how their intentions and demographic, economic, political, environmental, and physical conditions can lead to LUCC. While various empirical studies have been applied to analyse this phenomenon there still a gap in the literature concerning the capability of modelling approaches to provide applied answers for determining LUCC based on farmers' intentions (which can be captured by interviews).

Over the past two decades, modelling systems linked to artificial intelligence have been used to understand LUCC (Mishra et al., 2014; Pontius et al., 2004; Veldkamp and Lambin, 2001). Dynamic modelling sought to overcome the existing limitations of geographic information technologies that were permanently stationary at two-dimensional perspectives (Burrough, 1998). In the last years, complex systems have provided enormous potentialities for land-use modelling (Batty and Torrens, 2001), addressing and incorporating predictable and unpredictable changes. Spatial simulation modelling allows quantifying the changes of land use classes (Liu et al., 2008), predicting future land use patterns, providing an exceptional platform to explore complex interactions between human and biophysical systems (Gimblett, 2005). Complex phenomena are dynamic and comprise interdependencies through several aggregation stages. Currently, there is a broad range of mathematical models used, e.g., CA-Markov chains, ANN, logistic models of diffusion, and ABM. The firsts are more efficient for modelling spatiotemporal phenomena focused on landscapes, and land-use transitions, whereas agent-based models are more focused on human actions (Munthali KG, 2012; Parker et al., 2003). Even though complex science may help to understand the unpredictability of LUCC (Allen, 1997; Batty and Torrens, 2001; Portugali, 2006). However, its integration into the political instruments is still at the beginning (Chettiparamb, 2006) and difficult to apply, mainly due to many institutional barriers (Brömmelstroet and Bertolini, 2010).

Coupling LUCC models and spatial scenarios is a valuable task since it allows to indicate perceptions about alternative futures, and hypotheses. Scenarios are seen as a method to envisage future options linked to dynamic actions and to manage future uncertainties. Spatial scenarios can be used as tools able to translate complex targeted information to policy-makers and the public. They can provide strategic support for decision-makers and researchers to evaluate potential future alternatives, identify multiple planning strategies, and to support the impacts of the strategic options. Different methods and tools have been proposed and used with implications for environmental assessment and land use management. In land-use management, scenarios have been used to analyse feedbacks from urban growth, urban form and agricultural land-use changes.

As a case study for our empirical analysis, we choose Torres Vedras (covers an area of about 407 sq. Km.), in Portugal. Torres Vedras had, in 2011, a population of 79,465 inhabitants and is located in a peri-urban area near Lisbon (50 km) dominated by forest and agricultural land. In the last decades has been suffering considerable urban pressure. Between 1995 and 2010 registered an artificial surface increase of 41%.

Agriculture activity (e.g., fruits, vegetables and wine) has been an essential sector in this municipality (Statistics Portugal, 2011). However, in the past few years, agricultural land has been declining, caused by many demographic and economic factors, such as a decrease in farmer population and in the used agricultural area, and a significant demand in urban development (Abrantes et al., 2016; Gomes et al., 2019b).

In the following, we will describe the research objectives, questions and hypotheses of this PhD research, as well as the methodological approach and thesis structure, will be presented.

Research objectives, questions and hypotheses

In this PhD thesis, we proposed three different LUCC models (CA-Markov, ANN-MLP, and ABM) to analyse and simulate future farmers' LUCC intentions for four different scenarios. They integrate geographical modelling, complexity science, land use science, and planning theory to recognise LUCC dynamics in a peri-urban context. According to this, the specific goals of our PhD research are:

1) To measure the impacts of urban growth on agricultural land over time;
2) To identify and predict different levels of agricultural land fragmentation, identifying its drivers;

3) To spatialize farmers' LUCC intentions according to the following scenarios (for the time horizon of 2025): A0 – current demographic, social and economic trend (BAU); A1 – regional food security; A2 – climate change, and B0 – farming under urban pressure;
4) To validate the achieved results according to stakeholders' LUCC expectations, through a participatory workshop; and
5) To propose the integration of spatial complexity analysis to support spatial planning at the local level.

These objectives aided to characterise the case study regarding the LUCC over time, and to better understand the behaviour of different drivers and actors, which have affected land transitions.

In addressing the above objectives, this PhD research aims to answer the following research questions and hypothesis:

1) What are the demographic, economic, political and environmental driving forces related to LUCC in Torres Vedras Municipality?:
2) How farmers' LUCC decisions and their motivations may affect land conversion in different scenarios? and;
3) How to help planners in the decision-making process, since LUCC in peri-urban regions occurs very fast?

According to these research questions, the following research hypotheses are proposed:

1) Urban growth has a significant impact on agricultural land decrease and fragmentation;
2) Social, demographic, economic, and political drivers affect farmers' LUCC intentions in different scenarios;
3) To engage stakeholders in the criticism of LUCC models' outcomes may be the key to propose land use planning recommendations more efficiently.

Methodological approach

To address the research objectives, questions and hypothesis presented above, we performed a step-by-step methodology used to achieve the proposed goals. We used a combination of LUCC analysis, geographical models, farmers' interviews, and a participatory workshop with local stakeholders, towards the creation of a consensual LUCC model for each scenario. According to the achieved results, we analysed and discussed the LUCC impacts for each scenario, and we addressed land-use strategies according to the specific impacts of each scenario.

Following, we described the main methodological research approach adopted throughout this thesis:

1) We developed a method (built in the NetLogo software tool), which we called LAND (Land-use chAnge and Neighbouring Distance) to measure the impacts of urban growth on agricultural land variation and agricultural land fragmentation over time, from the edge of existing urban areas;
2) We created a methodology using landscape metrics and cluster analysis to measure agricultural land fragmentation in the past, in the present and to predict agricultural land fragmentation in the future, and identifying its drivers;
3) We performed interviews targeted at currently active farmers to capture their LUCC intentions for four scenarios (for the time horizon of 2014-2025);
4) We simulated future LUCC, integrating demographic, economic, political, and environmental driving forces, and incorporating farmers' LUCC intentions, based on the CA-Markov, ANN-MLP, and Agent-Based Modelling (ABM) LUCC models; and
5) We organised a participatory workshop to validate and analyse the LUCC models' outcomes. The participants of this workshop were local stakeholders in the following main areas of land management: a) land use planning; b) real estate developer; c) agriculture; and d) forest.

The step-by-step methodology is shown schematically in Figure 0.1.

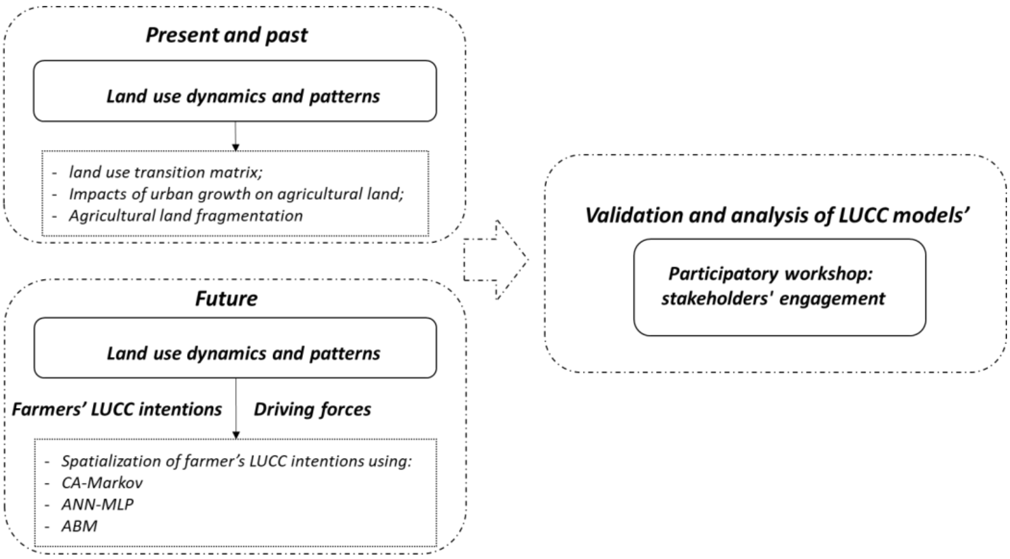

Figure 0.1 – Schematic step-by-step methodology.

Thesis structure

The PhD research highlights the dynamics of LUCC in a peri-urban area. This study identifies a multimethod perspective and involves complex and interrelated analysis. This PhD research has three parts and seven chapters, each part and each chapter developing a step-by-step towards to simulate LUCC under different scenarios. The outline is shown schematically in Figure 0.2.

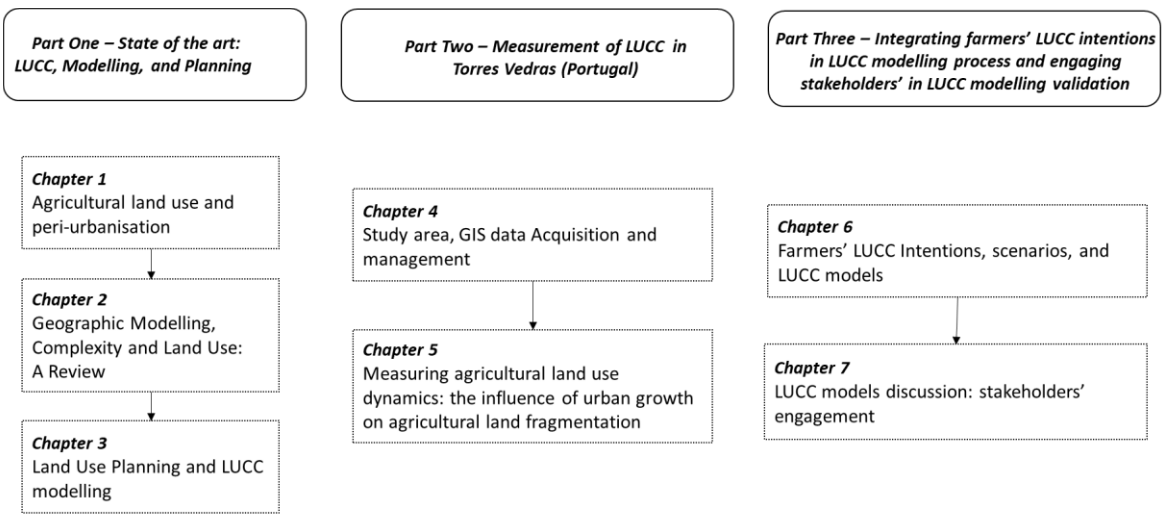

Figure 0.2 – Thesis organisation flowchart.

Part One is related to state of the art of LUCC, modelling and planning and includes chapter 1, 2, and 3. Chapter 1 outlines the agricultural land use and peri-urbanisation. We highlighted the concepts of land use/cover; peri-urbanization and land use/ cover; population and urbanisation in Portugal; and farmers' role on LUCC. In Chapter 2, we presented a framework of geographic modelling and land use in the context of the complexity science; and we identified the earlier studies on LUCC analysis, the geographical models and LUCC, and the link between complexity science and Geography in LUCC modelling.

Part two (the measurement of LUCC in Torres Vedras municipality) consists in two chapters (chapters 4 and 5). Firstly, in chapter 4 we introduced the Geographic Information Systems (GIS) data acquisition and management, and we contextualised the case study. In chapter 5 we measured the influence of urban growth on agricultural land fragmentation, in our study area, using different methods.

Part three includes chapter 6 and 7. It aims to integrate farmers' LUCC intentions in LUCC modelling process and engaging stakeholders' in LUCC modelling validation. In chapter 6, we presented different methods used to analyse farmers' LUCC intentions. We first presented the four explorative LUCC scenarios and the farmers' interviews, and secondly, we modelled the farmers' LUCC intentions using the CA-Markov, ANN-MLP, and ABM models. And in chapter 7, we presented an analysis that engages local stakeholders' in the process of LUCC models validation and discussion.

Finally, we identified the contributions of this PhD thesis to the field of knowledge, the limitations, as well as we recognised the challenges for future research.

Part One: State of the art: LUCC, Modelling, and Planning

Introduction PART ONE

Land use in peri-urban regions is in constant changing. To understand its spatial and temporal dynamics is of great importance in the study of land-use systems, and for land use planning.

Complexity science can help to deal with this analysis, identifying the uncertainties of LUCC and giving answers to the unpredictable LUCC. Every stage involves dynamics, relationships, emergence and unpredictability. Integrating complexity science and LUCC analysis in the land use planning to understand the land-use dynamics is one of the most significant challenges that planning needs to face in the future.

Part One investigates the theoretical literature regarding agricultural land use and peri-urbanisation, geographic modelling, and how complexity science can be integrated more permanently into land-use planning.

Chapter 1 – Agricultural land use and peri-urbanisation

Introduction Chapter 1

LUCC occurs in response to demographic, social, economic, and biophysical elements. In the last decades, the impact of human activities has grown affecting global, regional and local landscapes. Choices about LUCC have affected the land conversion from agriculture to urban uses, resulting in less land available for farming. Agricultural land is facing urban pressure in peri-urban regions. New strategies and efficient planning instruments to anticipate the effects of these pressures in these areas, as well as to implement strategies to minimise the urban expansion are needed.

Land use planning instruments comprise population growth projections, promote social and economic inclusion, identify the relationship between spatial planning and land use management system, and define the best options for land use occupation.

In this chapter, we explored the literature review about LUCC especially in peri-urban areas context, identifying its causes and consequences.

1. Land use/cover

Land use definition as a function only recently has become autonomous. In 1994, Food and Agriculture Organization (FAO) at the Convention to Combat Desertification (UN, 1994) defined land use as the area that incorporates all elements of earth's terrestrial surface such as soil, surface hydrology, vegetation, and human settlements. Its conception is the result of a complex interaction connected by all these elements (Robson and Berkes, 2011; Turner et al., 2007). Land cover, on the other hand, is associated with what is observable by the human eye in the field and satellite and aerial images (Comber et al., 2005). FAO (2011) recognised three main dimensions which are incorporated by the land-use system:

(1) environmental – includes greenhouse gas emissions, the productive capacity of land and ecosystems, air quality, water availability, and biological diversity;

(2) social – comprises price and supply of a national food basket, land access, water and other natural resources, labour conditions, rural and social development, energy access, human health, and safety; and

(3) economic – includes economic growth, economic viability and competitiveness, technology access, technological capabilities, and energy security.

As a science, land use (also called land-change science and land-system science) is the study about the changes and impacts at the interface of these three previously mentioned dimensions (Ii et al., 2007; Verburg et al., 2013). It emerged as a sustainability science by encompassing multiple disciplines with a connection to human and natural sciences (Zscheischler et al., 2017).

Forest, agricultural systems and urbanisation processes are the main fields studied by this science, being its analysis critical for land use management (Alexandratos and Bruinsma, 2012; Batty and Longley, 1986; Hyde et al., 1996). They are the basis for economic, social and environmental diversification in rural and urban communities. Decision-makers, stakeholders, and researchers have demonstrated concern about its changes and undesired consequences (Schreinemachers and Berger, 2006). Accurate, reliable and timely data on global trends in land-use dynamics are relevant for evaluating present and forthcoming needs and for setting policy priorities to endorse inclusive and equitable development. Below we describe each one of these fields regarding its distribution and importance both globally and in Europe.

1.1 Forest land

In 2015, forest land covered around 31% of the world land (over 4 000 million hectares) (WB, 2019). In the European Union covers approximately 36% (representing more than 161 million hectares of the total area). Ecologically, Europe's forest land belongs to many different biogeographical regions, in which 42% of this forest is composed by coniferous, 40% is a mixed forest, and 18% are broadleaved (EEA, 2018).

Forests are ecosystems that have relevant environmental functions, to serve as habitat for a diversity of plant and animal species (Berg et al., 1994), to prevent landslides (Dhakal and Sidle, 2003), avalanches in mountainous regions (Feistl et al., 2015), and to filter water supplies (Hallema et al., 2018). Alongside its environmental profits, forests provide mainly wood, and other resources such as energy (Röser et al., 2008), forage for animals (Pabian et al., 2012), and opportunities for tourism and recreation (Ohe et al., 2017).

Forests face several threats, such as droughts, fires, and pests. However, one of the main threats responsible for its reduction have been the agricultural expansion. Globally, in the last decades, 30% of the forest was converted to agricultural use (Barbier, 2004; Ramankutty et al., 2008), and more than 50% in the tropics (Gibbs et al., 2010). Furthermore, agricultural expansion and intensification have led to an increase in forest land fragmentation (Haddad et al., 2015; Ligtenberg et al., 2001). To counter this trend, the United Nation has been promoting its preservation by defining global aims such as to preserve and reverse the loss of forest cover worldwide and improve forest-based social, economic and environmental benefits.

1.2 Agricultural land

Agricultural lands are another of the significant biome on earth, occupying around 30% of the global ice-free land area (Ellis and Ramankutty, 2008), and constitute the major livelihood for 40% of the world’s population (WB, 2019). By 2050, human populations are projected to grow to nearly 10 billion (UN, 2017) increasing pressure on agricultural land to meet the demands for food by future populations.

In Europe, agricultural land corresponds to almost half of the territory (48%). In the European Union, the total agricultural area used (UAA) was around 179 million ha in 2016. France had the most significant agricultural area with 29 million ha, followed by Spain (24 million ha), and by the UK and Germany (both with 17 million ha). In total, around 19 million hectares (11% of UAA) were potentially irrigable in 2013, located mostly in Southern Europe, namely in Malta (33.6% irrigated land of total UAA), followed by Greece (24%), Italy (23.7%), Cyprus (22.6%), Portugal (13.1%), and Spain (12.4%). Irrigation allows farmers to extend the growing season into the dry season. However, the irrigated land is one of the major cause of freshwater eutrophication, which indicates the pressure of these areas on water resources (Eurostat, 2013). Beyond this, other impacts from the environmental point of view can be pointed out to agricultural practice such as greenhouse gas emission (Oertel et al., 2016), biodiversity loss (Kok et al., 2018), losses of soil quality (Bayramin et al., 2008), and change of local and regional climates (Zhang et al., 2017).

From this perspective, agriculture is one of the main responsible for environmental degradation, and its impacts are expected to rise in the future due to the projections of population increase and per capita consumption (UN, 2017). However, from the urban growth perspective, urbanisation is one of the main threat for agricultural land consumption (Morgado et al., 2017; Weber et al., 2018), particularly in the peri-urban regions (Gomes et al., 2018; Mazzocchi et al., 2017).

1.3 Urban land

Globally in 2019, more than 50% of the world’s population lives in urban areas, in which one people in eight live in the 28 mega-cities bigger than 10 million inhabitants, mostly located in the global South. By 2050, more than 60% of the world’s population is expected to live in urban areas (WB, 2019).

Currently, North America is the region where more people live in urban areas (82%), followed by Latin America and the Caribbean (80%), and Europe (73%). By countries, China has the most prominent urban population (758 million), followed by India (410 million), and the United States of America (263 million). Moreover, by cities, Tokyo is the world’s biggest city with 37 million inhabitants, followed by New Delhi with 29 million, and Shanghai with 26 million inhabitants (WB, 2019).

The urban population worldwide has overgrown since 1950, from 746 million to 3.9 billion in 2014. By 2050, it is expected to reach 6.3 billion, with approximately 90% of the growth concentrated in Africa and Asia.

The urbanisation process historically has been related to economic and social growth. These significant phenomena of the XX century evolved from a contiguous growth around the city, and along highways and roads, connecting the suburbs (Salvati et al., 2018) in different forms. Enlarged cities (Gaspar, 1999; Pereira and Silva, 2008), metapolis (Ascher, 2010), city-regions, or periurban regions, are some of these forms, characterised by continuous population growth, frequently fragmented areas and located in the mix between urban-rural settlements, and economic activities (Allen, 2003).

In Europe the urbanisation process took place quickly since 1950, but since the 1990s moderated its pace. Currently, in the European Union, there are over 800 cities, with more than 50,000 inhabitants, in which about 90% are small and medium-sized cities (between 50-250,000 inhabitants). Europe's urban areas have different morphological types, in which can be recognised as monocentric (distributed over extensive areas), dispersed (scattered cities), linear (with linear forms of agglomeration), and polycentric urban region (multiple cities connected) (Waterhout et al., 2005).

To harmonise the metropolitan area definition, Organisation for Economic Co-operation and Development (OECD), European Commission (EC), and Eurostat defined it as a functional economic united categorised by densely populated areas over 50,000 inhabitants and commuting zones. In 2017, the most densely populated metropolitan regions in European Union were London (14.2 million), followed by Paris (12.2 million), Madrid (6.5 million), Barcelona (5.5 million), and Berlin (5.2 million) (Eurostat). The metropolitan regions of the European Union are the motor of the economy representing 62% of its jobs, and 67% of gross domestic product (GDP).

2. Peri-urbanisation and agricultural land use

Urbanisation is one of the significant phenomena affecting the loss of prime agricultural land as a result of a demand for land around urban cities (Weber and Puissant, 2003), resulting in more frequent land tensions between urban and agricultural areas (Gardi et al., 2015). These pressures occur mainly in peri-urban regions, where transitional and competitive areas between urban and rural areas are recognised (Errington, 1994). Peri-urban regions are viewed as an intermediate area between urban-rural settlements with rural identity (Biegańska et al., 2018; Tedesco et al., 2017). They are frequently identified by the emergence of urban activities close to urban centres (Guastella and Pareglio, 2016), and a likely place for living, recreation or even for work (Brinkley, 2012; Hornis and Van Eck, 2008).

Several typologies have been implemented by many researchers to characterise peri-urban areas. They have been classified since large residential areas, high population growth, intensification of residential areas, urban infrastructure, and services, coexistence between farming activities, and fragmented areas (Choy and Sutherland, 2008). In 1955 Spectorsky presented the concept of exurbanization (Nelson and Dueker, 1990). This concept is defined as the ring of wealthy rural communities inhabited by urban professionals who commuted to the urban city for work. Currently, these areas could also be called as suburbanization (Arthur and Thomas, 1999), in the perspective of an ever-widening city. Another closely related concept is counter-urbanisation. This concept suggests an increase in the migration away from the city to the countryside, as well as the relocation of services and industries (Fielding, 1982). Champion (1989) refers that counter-urbanisation is a tendency towards de-concentration, resulting from a complex pattern of flows.

Migration dynamics, transport accessibility, economic and demographic development are important drivers (Geist and Lambin, 2006), leading to the emergence of urban sprawl. This is one of the land-use patterns related to peri-urban morphology (Bretagnolle et al., 2001; Debbage et al., 2017; Salvati and Carlucci, 2016; Stomp, 2013). Urban sprawl is defined as a low-density dispersed development outside the compact urban area and beyond the edge of service and employment (Gennaio et al., 2009). Batty et al. (1999) defined urban sprawl in three interconnected concepts of spatial dynamics: (a) the decline of central or core cities; (b) the emergence of edge cities; and (c) the rapid suburbanization of the peripheries of cities.

Moreover, Torrens (2000) defined urban sprawl as low-density growing along the fringes of the metropolitan areas, and is characterised by its compactness and dispersion. It is also identified as the urban expansion into the suburban areas and categorised by unplanned (EEA, 2006), uneven growth (Oueslati et al., 2015), contiguous suburban growth (Logan and Crowder, 2002), mixed uses (Bengston and Youn, 2006), scattered and leapfrog development (Torrens and Alberti, 2000), strip or linear development, poly-nucleated nodal development (Galster et al., 2001), and both as a state, and a process (Jaeger et al., 2010).

One of the main concerns regarding the urban sprawl and expansion of peri-urban areas is the loss of productive agricultural land, verified in the transitional zones between urban and rural areas. The agricultural land in this area can suffers from urban pressure. However, they can benefit from the market's proximity.

2.1 LUCC drivers

LUCC occurs as a consequence of both natural and human activities (Lambin et al., 2001; Marty et al., 2014; van Vliet et al., 2015), triggered by driving forces. The concept of driving force became well-known in landscape ecology during the 1990s (Bürgi et al., 2004; Eiter and Potthoff, 2007), in which were defined the processes responsible for the landscape changes (Bürgi et al., 2004). The driving forces, process and manifestations that influence LUCC, particularly agricultural land-use change, according to van Vliet et al. (2015) can be categorised as follows:

i) underlying drivers (e.g., environmental, policy, technology, socioeconomic, culture, and location);
ii) LUCC process - related to land manager decisions and farmer profile; and
iii) manifestations of agricultural land-use change - connected to intensification (e.g., increase in agricultural land area), and disintensification (e.g., land abandonment) (Fig. 1.1).

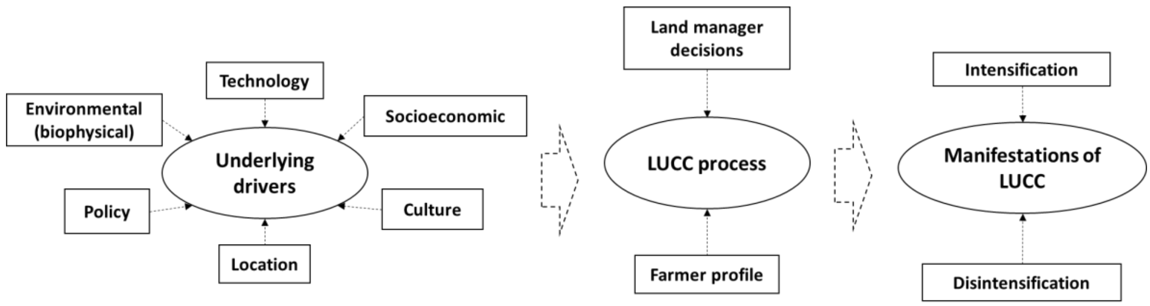

Figure 1.1 – Underlying drivers, LUCC process, and manifestations of LUCC (adapted from van Vliet, 2015).

Worldwide, in the last three decades, almost 3% of semi-natural land has been converted to other land cover types (OECD) (e.g., croplands, and urban development). This has been contributed to the loss of ecosystems, land fragmentation, increase of flood risk vulnerability, air, noise and light pollution, and to the decrease of green spaces.

Table 1.1 reviews some of the key global, national, and local driving forces responsible for the LUCC at different scales.

Table 1.1 – Global, national and local driving forces.

Scale	Driving force	Description	Source
Global	World prices	It can influence LUCC decisions.	(Golub et al., 2009)
	Climate change	It represents unpredictability - greater negative impacts.	(Dale, 1997; Pielke, 2005)
	High energy prices	It increases food price.	(Steinbuks and Hertel, 2013)
National	Urbanisation	It changes the food demand.	(Matuschke, 2009)
	Shortening market chains	It reflects a stricter price.	(Bren d'Amour et al., 2017)
	Water scarcities	It promotes strategies to create irrigated agricultural land.	(de Espindola et al., 2012)
Local	Population pressure	It can reduce the agricultural land available for farming.	(Gomes et al., 2019a)
	Technology	It can increase agricultural productivity.	(Corbelle-Rico et al., 2015; Springer and Duchin, 2014)
	Market access	It can improve output markets.	(Hettig et al., 2016)

In Europe, the landscape has been experienced significant changes in LUCC. Over the past century, Europe almost doubles the population from 288 million at the beginning of the last century to 513 million in 2018 (Eurostat). These dynamics were encouraged by different drivers such as political reasons, cultural history, land reforms, enhancing technological, as well as a diversity of institutional and economic drivers (van Vliet et al., 2015). The population growth and the need for cropland, grassland, and forest have been leading to a high level of LUCC. However, these dynamics are not homogeneous over Europe, which have been influenced by natural (e.g., precipitation, relief, and temperature), and socioeconomic characteristics (e.g., two world wars and different economic and social systems).

In Portugal, the main activities, implemented since the first half of the 20th century, that have led to significant land use transformations, have been the rural wood-gathering, agriculture, and livestock production (Pinto-Correia and Vos, 2004). In the last decades, the main responsible for LUCC was accompanied by an extensive drop of cropland by conversions into grasslands and forest (particularly in Alentejo region) (source data: DGT, 1995, 2010). However, in the last few decades, former cropland has been abandoned due to migration, market competition and urbanisation (Antrop, 1993). These interactions and dynamics over time have provided a cultural self-sustainable system (Blondel and Aronson, 1999).

2.2 Drivers in peri-urban areas

Urban areas are the main settlement of human activities. In the last years, several researchers have been discussing the driving forces of urban expansion in peri-urban areas that have been shaping Europe. Below, we present some of the drivers, that we will use in our empirical study.

Lambin et al. (2003) identified some of these drivers such as the resource scarcity; the change of diagnosis produced by the markets; the policy interference; the loss of adaptive capacity; and the changes in social organisation. In its turn, Quan (2006) identified industrialisation, infrastructure, agricultural intensification, and policy as the main driving forces responsible for LUCC.

The urban expansion in peri-urban areas has implications for land use (Abrantes et al., 2016; Lambin et al., 2003; Wu et al., 2010), both in the socioeconomic and environmental perspective (Bhatta, 2010), and they can be both negative and positive. The negative impacts are, for instance, the undesirable effects on public health and quality of life (Jackson and Kochtitzky, 2003), increased urban pollution (Nechyba and Walsh, 2010), greater dependence on cars (Owusu, 2013), spatial fragmentation (Haregewoin, 2005), and loss of farmlands (Bhatta, 2010). The positive aspects are the sense of community between the inhabitants (Arbury, 2005), more living space (Bhatta, 2010), decreasing crime rates (Owusu, 2013), and fragmented urban growth has been perceived as economic expansion (Oueslati et al., 2015).

Agricultural land has always been, and remains, an economic, social and culturally significant part of life, and has been of vital importance in response to the preservation of environmental and landscape values (Kizos et al., 2010), to preserve the quality of food in urban markets (Paül and McKenzie, 2013), and to contribute to mitigate urban expansion (Coisnon et al., 2014). The areas located on the urban fringe are frequently under pressure due land competition and scarcity, and often leading to farmland fragmentation (Jiang et al., 2013), and agricultural production decrease (Hualou and Jian, 2010). This is one of the main barriers that agriculture is currently facing in many urban regions (Campbell, 2015; Kuemmerle et al., 2006).

Recent studies have described how it can contribute to the loss of natural land and wildlife populations, modifications in local climate, flora, and fauna (Haddad et al., 2015; Matthew et al., 2015; Senthilkumar et al., 2009), and loss of agricultural productivity (Alfiky et al., 2012). Land conversion divides farmland parcels into smaller, and more isolated ones (Haddad et al., 2015). One of the significant consequences of this division is the decrease in terms of productivity and quality of the agricultural products (Latruffe and Piet, 2014), thus increasing the costs of reconnecting separated habitats (Prugh et al., 2008).

Many drivers influence these dynamics over time in peri-urban areas. They are controlled by five main drivers such as political, demographic, economic, social, and environmental drivers, as a result of land supply and demand, and affecting its patterns, structures, and functions.

Over the past few years, some studies have contributed to describe the effects of landscape change (Abdollahzadeh et al., 2012; Sklenicka, 2016; Su et al., 2014; Xiao et al., 2013) and to understand its drivers (Alexander et al., 2015; van Vliet et al., 2015). They encompass a wide range of drivers such as technological, recreational, tourism, landscape protection, cultural (Bürgi et al., 2017; Eiter and Potthoff, 2007; Plieninger et al., 2016), agricultural intensification (Quan et al., 2006), transport infrastructures (Galster et al., 2001; Irwin et al., 2007; Levia, 1998; Nechyba and Walsh, 2010; Torrens and Alberti, 2000), and land price (Nickerson et al., 2012). They together, in a complex interactions process, are the mechanism that leads to LUCC (Bürgi et al., 2004; Busck and Kristensen, 2014).

As shown, there are plenty of driving forces responsible for LUCC. One of the most widely studied is the land price. This driver has been studied over the years by several researchers alike since the initial studies of Adams et al. (1968), Clonts (1970), Fallah et al. (2012), Hushak (1975), and Hushak et al. (1979), analyzing several indicators that can influence the land prices. Complex interactions among landowners and urban developers lead to increase in farmland prices (Nickerson et al., 2012). Capozza and Helsley (1990) and Plantinga et al. (2001) presented one of the first works in this area, identifying the market price land as a valuable index in the decision. Landowners have the choice to rent or not to rent, buy or not to buy, sell or not to sell (Ettema et al., 2007; Koomen et al., 2007). Economic theory specifies that land values are equal to the number of expected returns (Pope, 1985), being the relation between land price, land income, and discount rate. Capozza and Helsley (1990) created a schematic diagram to illustrate urban and agricultural land prices and rents as a function of distance to city centre (Fig. 1.2), demonstrating that urban growth affects urban and agricultural land prices.

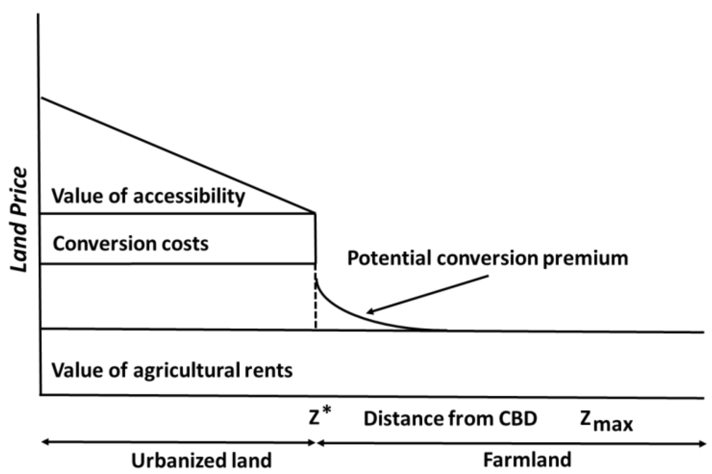

Figure 1.2 – Land prices and distance to the city centre (adapted from Capozza and Helsley, 1990).

Several researchers have identified other drivers that have been influencing land price in peri-urban areas such as water (Ding, 1999), negative externalities of urban development (e.g., air and water pollution), and land preservation (Brueckner, 1990; Engle et al., 1992).

3. Farmers’ role on LUCC

Progressive land-use changes – from agricultural land into urban land – generate new challenges and opportunities. Land agents are motivated by different interests and pursuing different strategies such as: (1) speculators or developers, who are waiting to take advantage of urban development and obtain the highest profit margin (Bhatta, 2010; Brown et al., 1981); (2) farmers, who are affected by urban development and intend to capitalize on their investment (Ettema et al., 2007; van Vliet et al., 2015); and (3) farmers, who opt to own a land property for the amenity qualities and for a higher life quality (Paül and McKenzie, 2013; Valbuena et al., 2010b). Despite the specific objectives of each actor, they are most of the times influenced by emotional intentions that may affect their decisions (Jiang, 2007; Jiang et al., 2007; Loewenstein and Lerner, 2003).

Farmers decisions and their participation in land markets as buyers, sellers, developers, and renters (Berger, 2001; Fazal et al., 2015; Kaiser and Weiss, 1970) have consequences for land use conversion. They play a crucial role in making decisions (Ettema et al., 2007), and they can supply financial investment and control future land use occupation (Lubowski et al. 2008).

Those who manage the land, in peri-urban areas face challenges arising from the proximity of land to an urban centre. Some descriptive studies have been done to analyse decision-making processes on peri-urban areas (Berry 1978; Heimlich and Anderson 2001; Heimlich and Barnard 1992). Urban pressures present farmers with the choice between maintaining their agricultural activities and maximising the production potential of their crops or selling their farmland to land speculators. Lopez et al. (1988) analyse this dichotomy and Heimlich and Anderson (2001) evaluate the behavioural response of peri-urban farmers regarding urban development, income from agricultural production, agritourism, and off-farm employment. Capozza and Helsley (1990) consider the influence of uncertainty about future land rents as the best opportunity to transform farmland into urban development. These studies propose that land use transformation occurs when the value of expected urban development rents exceeds the value of agricultural rents.

Farmland location is a determining factor for economic sustainability. Different drivers influence agricultural profitability and land valuation. Drivers such as farmland proximity to other farmland, ready access to the transport network, proximity to agricultural cooperatives, proximity to the urban growth boundary, commercial markets (imports, exports), and large consumers (Livanis et al., 2006), water costs (Ding, 1999), negative externalities of urban development (e.g., rising prices, and air and water pollution), and growth control instruments (e.g., land preservation measures) (Brueckner, 1990; Engle et al., 1992) can be determinants in the land-use conversion.

Different actors have different goals on land management issues. Real estate speculation is crucial to those who appreciate land values. Land-use conversion is linked to landowners' decisions and their participation in land markets as buyers, sellers, and developers, and on tenants to their involvement in land rent market. They play a fundamental role in what will take place in the land use in the future (Ettema et al., 2007), and they can supply financial investment and control future LUCC (Lubowski et al., 2008). The conversion of natural land to artificial surfaces must always have the approval of the policymakers (Bryant et al., 2010; Fazal et al., 2015; Valbuena et al., 2010b). They verify the viability of proposed projects and if conflicts with strategic spatial planning defined for a specific area. These strategies involve the control of land in its size, structure, and in the intention to preserve the biodiversity.

Understand actors' behaviours, identifying their intentions regarding land management under different scenarios is relevant towards a better land use management in the future.

4. Population and urbanisation in Portugal

Population growth has been in the early stages the push factor of urbanisation in Portugal. People from rural areas moved to the cities especially to the metropolitan regions of Lisbon and Oporto (mainly in the 1960s), who migrated due to the expectation to find better opportunities. These areas are mostly characterized by high population density, and very tertiarised (Statistics Portugal, 2011). The total population in mainland Portugal more than double between 1864 (first general population census) and 2011 (15th population census). From 4.3 million inhabitants to over 10 million inhabitants in 2011 (Statistics Portugal, 2011). This population is mainly concentrated in the coastline from Viana do Castelo to Setúbal, and along the Algarve region coast (EEA, 2006; Gomes, 2017). Urbanisation was more intense in the decade of 1980s and 1990s mainly in the two metropolitan regions, characterised by a clear polycentrism (Carmo, 2013). According to the work developed by Abrantes et al. (2019), the majority of the municipalities in these two metropolitan regions are characterised by urban sprawl forms. The spatial patterns of urban development in Portugal have registered significant changes over the last decades. The evolution of land use pattern has occurred mainly in the fringe of these two metropolitan regions, and have involved changes from agricultural land into artificial land, mostly to residential and tourist settlements, industrial, and commercial surfaces.

Land use evolution: 1995-2010

In 2010, mainland Portugal was mostly covered by forest and semi-natural areas (54.47%), followed by permanent crops and heterogeneous agricultural land (21.84%), non-irrigated land (6.37%), pastures (5.16%), artificial surfaces (5.11%), permanently irrigated land (5.03%), and by water bodies and wetlands (2.01%) (Fig. 1.3 and Table 1.2).

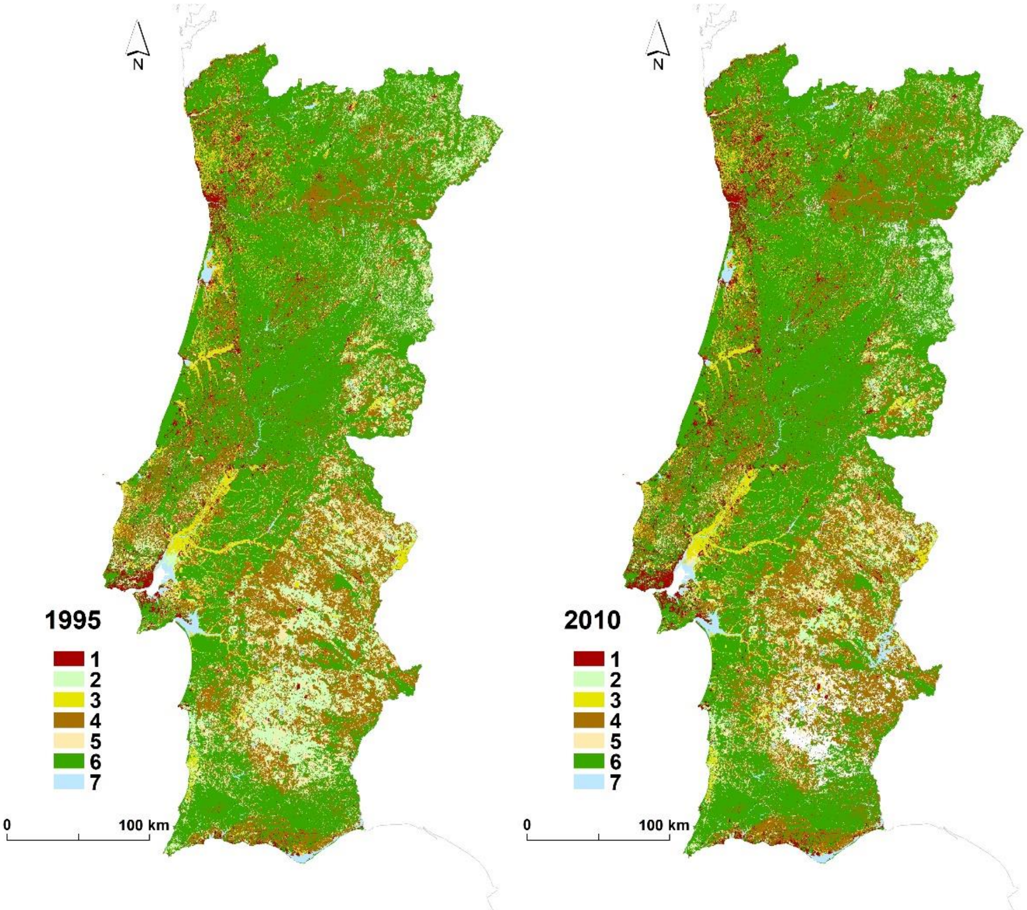

Figure 1.3 – Land use/cover in 1995 and 2010 in mainland Portugal. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2010).

Table 1.2 – Land use/cover in 1995 and 2010 (%) in mainland Portugal. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2010).

Year/ LUC	1	2	3	4	5	6	7
1995	3.82	9.93	4.89	22.00	7.24	50.48	1.64
2010	5.11	6.37	5.03	21.84	5.16	54.47	2.01

The Portuguese agricultural sector evolution suffered many changes during the last decades. It experienced a continuous decrease of agricultural producers, from 550,000 in 1989 to 278,000 in 2009, and a decline of the utilised agricultural area was registered in the same period, from 4.1 to 3.5 million hectares.

During 1995 and 2010 significant LUCC occurred. All agricultural land use classes decreased during this period, while forest and semi-natural areas and artificial surfaces increased.

Artificial surfaces, from 1995 to 2010, increased as a result of the loss of forest and semi-natural areas (51,936 ha), permanent crops and heterogeneous agricultural land (29,183 ha), and permanently irrigated land and pastures (more than 10,000 ha each) (data source: DGT, 1995, 2010). Moreover, the increase of forest and semi-natural areas were verified as a result of the loss of all agricultural land use classes (Table 1.3).

Table 1.3 – Cross-tabulation of land use/ cover between 1995 and 2010 in mainland Portugal. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2010).

1995\ 2010	1	2	3	4	5	6	7	Total (ha)
1	333047	8037	10289	29183	10211	51936	371	443074
2	47	455061	12203	29988	41809	11596	8	550712
3	83	33615	359876	26504	8730	7303	20	436131
4	169	80187	27923	1651908	24546	106788	10	1891531
5	46	71415	6198	24584	331998	12778	4	447023
6	2782	75220	15301	156625	194704	4272644	303	4717579
7	273	4153	998	8957	5429	9853	144388	174051
Total (ha)	336447	727688	432788	1927749	617427	4472898	145104	8660101

Driving-forces

Physical, environmental, demographic, social, economic, cultural and political conditions have influenced the land use patterns both temporarily and spatially in the past few decades in Portugal. Some works have been published related to the driving forces that have been responsible for LUCC in Portugal. For instance, the works developed by the LANDYN Project (DGT, 2013) and Meneses et al. (2017), analysed the entire territory; De Brum Ferreira (2001) studied the Alentejo region; Teixeira et al. (2014), analysed the central region of Portugal; and Moreira et al. (2001) and Pôças et al. (2011), studied the driving forces responsible for the LUCC in the North of Portugal. These studies identified that the main driving forces that influenced the evolution of artificial surfaces in the past few decades were the gross domestic product, resident population, and employed population in the tertiary sector. The land conversion to artificial surfaces has been one of the greatest LUCC occurred in Portugal in the last few decades with negative impacts for the environment. Moreover, the drivers that were identified as the main responsible for the agricultural land-use changes have been the gross domestic product, the employed population in the primary sector, and the European agricultural funds. And lastly, the driving forces that have been the main responsible for the forest land change, in the last decades, are the fires, gross domestic product, European funds, and the employment (Beilin et al., 2014; Jones et al., 2011; Ribeiro et al., 2014).

Conclusion Chapter 1

LUCC is a complex conversion process. LUCC is the result of interaction in space and time between environmental and human dimensions. It is considered as the most significant issue that has more impacts on physical and social aspects. Thus, LUCC plays an essential role in the livelihood of communities.

In this chapter, we examined the land use/cover, particularly in peri-urban regions, identifying the main actors, the drivers, and the main causes and consequences of the LUCC in these areas. In the next chapter, we will explore how geographic modelling can be applied in the LUCC analysis.

Chapter 2 – Geographic Modelling, Complexity and Land Use: A Review

Introduction Chapter 2

Complexity theory as a new science, with roughly 50 years of age, had gradually advanced in the past decades. It integrates interdisciplinary subjects, such as networks and graphs, fractals, self-organising systems, chaotic and cybernetic systems. Geography has emerged as an essential field to describe, to understand, and to explain connections between human and physical interactions in space and time.

This chapter discusses and introduces the bridge between the classical geographical models and the modelling techniques. We presented some theories which have taken a view of geography as a complex social process. The purpose of this chapter is to identify current approaches to understand and to explain geographical procedures.

Chapter 2 outlines a theoretical overview of landscape ecology, geographical models, and complexity science. Firstly, in landscape ecology, we identified its emergence and importance in the study of LUCC. Secondly, we presented some of the most widely cited geographical models. And finally, considering the complexity science, we recognised how this science can be useful in the study of LUCC.

1. Earlier studies in LUCC analysis

The study of the landscape was firstly introduced in the researches of Alexander von Humboldt (1769-1859), Charles Darwin (1809-1882), Alwin Oppel (1849-1929), and Paul Vidal de la Blache (1845-1918). It was with Vidal de la Blache, a French geographer that the study of landscape incorporates not only natural conditions but also lifestyle ('genre de vie'), and settlement patterns, implying composition, structure and function of landscapes. Since then, the landscape became a central subject in geography. Landscape methods such as field surveys, maps, and terrain photographs have been helping in its analysis and interpretation. Nevertheless, it was only with the first use of aerial photography (after the First World War), that landscape gave the first steps, over the bird's-eye perception. This allowed the analysis of complex patterns (Davis et al., 2016; Turner, 2005).

During the 1960s and 1970s, when geostatistics was firstly applied, landscape studies became old fashioned. However, in the following decade, the Dutch WLO (The Dutch Association for Landscape Ecology) revitalise this science. Since then, landscape studies have been studied by ecologists, which focused their analysis on ecological processes, by geographers in the analysis of the relationship between the space, heritage and social aspects, and by architects which concentrated their studies on scenery.

Due to different meanings attributed to the landscape by the inter and transdisciplinary sciences UNESCO (The United Nations Educational, Scientific and Cultural Organization), World Heritage and the European Landscape Convention introduced two formal definitions. In 1996, UNESCO defined landscape has an interaction between nature and humans, reflecting the evolutions of society and settlement over time, influenced positively or/and negatively by physical, social, economic and cultural aspects. In its turn, the European Landscape Convention defined the landscape as perceived by people as a result of multi-interactions between environment and population (Council of Europe 2000).

Since 2000s new landscape networks have emerged such as Landscape Europe, Landscape Tomorrow, and UNISCAPE. They aimed to apply scientific research into planning and managing landscapes, often supporting education and training at different scales. Since the 2000s, landscape ecology has made successive progress in both a practical and theoretical perspective. Wu (2013) enumerated the ten most recent advances in landscape ecology namely in (1) the study of pattern–process–scale relationships of landscapes; (2) connectivity and fragmentation; (3) scale and scaling; (4) spatial analysis and landscape modelling; (5) LUCC; (6) history and legacy effects; (7) climate change interactions; (8) ecosystem services in changing landscapes; (9) landscape sustainability; and (10) accuracy assessment and uncertainty analysis.

LUCC has been studied in landscape ecology (Cen et al., 2015; Hietel et al., 2004), Geography (Musa et al., 2017; Sirami et al., 2010), and Economy (Shi et al., 2018; Triantakonstantis and Mountrakis, 2012; Walker, 2001), incorporating driving forces to identify its connections (Heistermann et al., 2006). The analysis of spatial morphology, structure, location, distance, linkage, and evolution, studied in landscape science, are fundamental to Geography. These analyses have been implemented using different methods. Several researchers such as Batty and Longley (1986), Triantakonstantis and Mountrakis (2012), Antrop and Van Eetvelde (2000), and White and Engelen (1993) have been analysed the spatial dimension of the landscape using fractal analysis and landscape metrics. Fractal analysis was firstly used by Mandelbrot in 1975 (1975) to study regular and irregular objects at different scales, whereas landscape metrics were firstly used in the 1980s to measure the fractal geometry (Mandelbrot, 1982). Both methods have been used to quantify the spatial heterogeneity of patches and to measure some spatial elements such as the size, patch density, fractal dimension, and edge density.

An extensive set of landscape metrics and spatial statistics approaches are available to quantify spatial patterns. They can be detected, mapped, and analysed integrating GIS techniques, such as a) the percentage of built-up areas that measures the dimension of built-up areas (in the percentage of the total area) quantifying the land use consumption (Sudhira et al., 2004). It is the ratio of the extent of the built-up areas, to the size of the total area of each unit. Some studies have been developed to analyse it, e.g., (Herold et al., 2003; Loibl and Toetzer, 2003); b) dispersion that quantifies the spatial distribution of patches (Hayek et al., 2011). It identifies the dispersed spatial arrangement and irregular and discontinuous fragmentation of patches (Burchfield et al., 2006; Salvati, 2014); c) urban permeation, which measures how far the built-up areas have extended through a given territory (Hayek et al., 2011). It estimates the degree of permeated settlement areas (Hayek et al., 2011); d) density, that quantifies the average of patches (Torrens and Alberti, 2000); e) clustering, quantifying the occupation of a small part of the land area in a developed area (Gordon et al., 1997); f) centrality, which corresponds to the distance from residential and no residential areas to Central Business District (CBD) (Bhatta et al., 2010); g) weighted urban proliferation, that corresponds to the product of the dispersion of the patches (Jaeger and Schwick, 2014); and for instance, the h) metric of utilisation density, which measures the number of people working or living in a built-up area (per km^2). Built-up areas with more workplaces and inhabitants are considered more intensively, than in areas with a lower density or workplaces, and or inhabitants (Bernstein and Shierholz, 2014; Paulsen, 2012).

These, as well as a wide range of other landscape metrics and methods, allow to measure landscape performance and contributes to analysing land use impacts. Along with these different methods, other approaches have been used to analyse LUCC. LUCC models are one of the most widely used approaches. In the next section, we will explore in detail the different LUCC models mentioned in the literature.

2. Geographical models and LUCC

LUCC models theorise, explain and create a mental abstraction of a land-use transformation in the future. They are used to recognise and describe the spatial analysis between people and environment, to apply advanced computational methods, to explore and test hypotheses based on geographic theory, to reproduce characteristics of the complex dynamics, and to reach and to understand human interactions (Heistermann et al., 2006; Verburg et al., 2006).

LUCC models seek to reproduce the real world and to identify behaviours to understand transition processes (Macal, 2016). In the last years, LUCC model's popularity has significantly improved due to upgraded computer power capabilities. They have been applied in many scientific fields, such as to understand the evolution, to develop hypotheses, and to make predictions. The modelling techniques have been asked to understand complex dynamics and to help decision-makers in the spatial planning process (Hersperger et al., 2018; Weber, 2003).

LUCC models have been developed since the 1950s and 1960s (Yu et al., 2011) to study the urban growth phenomenon. The analysis of the complexity of land-use systems involves a multidisciplinary assessment (Agarwal et al., 2002), and scientific knowledge (Magliocca et al., 2015; Wang and Li, 2011). They have been performed by a multidisciplinary assessment (Agarwal et al., 2002; Verburg et al., 2006) analysing the relationship between different types of behaviour to understand complex dynamics, and artificially recognise what can happen in the real world (Macal, 2016).

Different typologies of LUCC models have been identified in the literature. Several works, reviewing the existing LUCC models have been published in the last years. Lambin et al. (2000), focused their analysis on agricultural intensification models, in which divided in four categories: stochastic (e.g., transitional probability models); empirical-statistical (e.g., modelling spatial models); process-based (e.g., behavioural models and dynamic spatial models); and optimisation and dynamic simulation (e.g., deterministic and stochastic models). Moreover, Briassoulis (2000), classified LUCC models as econometric, optimisation, spatial interaction, and integrated models. Veldkamp and Lambin (2001) analysed the spatially explicit LUCC models. Additionally, Verburg et al. (2004) and Heistermann et al. (2006) focused their analysis on the characteristics of land-use systems. And more recently, Brown (2013) identified five key types of LUCC models: machine learning models, CA models, sector-based economic models, spatially disaggregated economic models, and ABM.

One of the most commonly accepted LUCC models division is proposed by Heistermann et al. (2006). They identified three different categories of LUCC such as geographic land-use models, related to land characteristics and suitability (Koomen and Stillwell, 2007); economic land-use models (Bouman et al., 1999), referred to economic theory; and integrated models, coupling different modelling approaches to better answer the research question (Hawkins and Nurul Habib, 2019). Table 2.1 described three of the most widely cited LUCC models in each of the three categories mentioned above.

Table 2.1 – LUCC models: geographic, economic, and integrated.

Category	Model	Description	Scale	Source
Geographic	**CLUE**	CLUE simulates future LUCC: deforestation, land degradation, urbanization, and land abandonment.	Global	(Verburg et al., 2002)
	DINAMICA-EGO	It supports the development of geomodelling applications.	National	(Oliveira et al., 2019)
	SLEUTH	It is a modified CA to simulate future LUCC.	Global	(Clarke, 2018)
Economic	**IMPACT**	It assesses alternative futures for global food supply, demand, trade, prices, and food security.	Global	(Rosegrant et al., 2008)
	CAPRI	It supports decision making related to CAP.	Regional	(Espinosa et al., 2016)
	MIRAGE	It is devoted to trading policy analysis.	Global	(Laborde and Valin, 2012)
Integrated	**LUMOCAP**	It evaluates LUCC and their impact on the rural landscape of the EU under the influence of CAP.	Regional	(van Delden et al., 2010)
	Nexus	It represents the processes of global agricultural intensification.	Global	(van Delden et al., 2010)
	MagPIE	It combines economic and biophysical approaches to simulate LUCC scenarios.	Global	(Popp et al., 2014)

2.1 LUCC in classical geographical models

Classical geographical models have in common the study of interaction, diffusion, migration and location, identifying who? what? why? and where?. They have been applied to represent land-use models (integrating principles of complexity theory) based on urban economics and social physics. Following, it is described seven of the most significant and widely cited theoretical models in geography related to land-use study such as (a) Von Thunen model; (b) Weber's model; (c) Walter Christaller's central place formulation; (d) Alonso's model (e) the gravity model of spatial interaction; (f) the Hagerstrand's model; and (g) Tobler's law.

(a) Von Thünen model: In 1826 Johann von Thünen published the first study based on this theory in *Der isolierte Staat*. Von Thünen model has three different conditions representing the agricultural situation around a city: a) isolation (isolated market); b) ubiquitous land characteristics (the land around the market is entirely flat and fertility); and c) transportation (there are no transport infrastructures) (Kanemoto, 1976). Von Thünen predicts agricultural land use based on concentric bands centred on the urban core, estimating land and transport costs (Kelly et al., 1996). As much closer to the urban core, the price of agricultural land increase (Parr, 2015). Consequently, the most productive agricultural activity is those located closest to the market, in which the Von Thünen model relates production and transport costs.

(b) Weber's model: After Von Thünen's model, more researchers have created more complex location models. Weber in 1909 established an approach for the place of manufacturing activities. Weber identified two principles: (i) the transportation and labour costs and; (ii) the optimisation of industrial location (Weber, 1982).

(c) Walter Christaller's central place theory: In 1933, Walter Christaller developed a theory that explains the location and the urban system dimension. This theory introduces a hexagonal lattice as an optimal mobility solution (Getis and Getis, 1966). The Christaller's central place theory comprises two main ideas: (i) threshold, in which the minimum population is critical to provide a good or service; and (ii) a range of goods or services, that represents the maximum distance that people can travel to purchase goods and services. Christaller's theory as the following main principles: (i) isotropic surface; (ii) regularly distributed population and resources; (iii) analogous purchasing power for all consumers; (iv) the transportation costs equal in all directions and proportional to distance; and (v) and no excess profits.

(d) Alonso's model: Years later, Alonso (1964) developed a new theory based on bid-rent, transports costs, and proximity to the city centre. Bid-rent is explained by an urban land-use process, that defines the decision-makers behaviours, and the money that the tenant pays. Alonso's model assumes that (i) transport is accessible in all directions; (ii) all employment, goods, and services are available at the city centre only; (iii) tax rates are uniform; and (iv) both buyers and sellers know the market.

(e) The gravity model of spatial interaction: It was designed in similarity with the physical law of gravitation (Isaac Newton - 1687). This gravity model predicts the best service location and analyses the distance, in which, people should travel to access to the specific service.

(f) Hagerstrand's model: Hagerstrand theory describes the distribution of economic or cultural characteristics in nebula-like clusters. This theory is based on the principle that farmers who had accepted the subsidies most recently tended to be the neighbours of previous adopters. This theory is found in three steps: (i) geographical proximity; (ii) the use of Monte Carlo or similar mathematical simulation techniques; and (iii) “the resistance concept”. These models presented an innovation in the study of the location theory and had been researched by many scientists over the last years.

(g) Tobler's law: *Everything is related to everything else. But near things are more related than distant things*. This sentence is the principle of the first law of Geography introduced by Waldo Tobler’s in 1969 (Miller, 2004). Tobler's law is based upon the friction of distance and the distance decay effect, where distance itself delays interaction between two or more places. This law was first applied by Tobler to urban growth systems and is related to spatial dependence and spatial autocorrelation (Tobler, 1970).

The above-mentioned geographical models have been the basis for many works in the field of land use science, supported by their theories and their experimental results (e.g., Wilson (1998), Phipps and Langlois (1997), White et al., (1997)).

2.2 The role of GIS and spatial analysis in LUCC models

GIS has emerged in the last few decades as an important science, using digital cartography, remote sensing, and database management (Burrough, 1986). GIS data can be shown in the vectorial and raster format. Vectorial data represents the real contour of objects, while raster data represents the object into discrete cells or pixels. The advantage of using raster data is mostly its easy management, using some procedures such as aggregation and comparison (Rocha, 2012).

GIS can use statistical spatial analysis techniques to manipulate and to create relationships between spatial data. It also enables integrate deterministic and stochastic predictive analysis establishing artificial relationships between different spatial data (Macal, 2016).

By the advantages mentioned above, GIS techniques were critical in the LUCC studies, in which multi-process approaches can be performed. These different processes can be achieved as follow: (i) identification of model's purpose; (ii) gathering data process; (iii) data preparation; (iv) variables selection and conversion; (v) processing and assessing; (vi) validation, and (vii) applying and maintaining the model. Below we describe the points (iv), (v), and (vi), in which GIS approaches were applied.

Variables selection

Sensitivity analysis identifies the connection between parameters and the state or time path of endogenous variables to the system (Lilburne and Tarantola, 2009), assessing the absence of systematic errors. This approach allows decreasing the dimension of the variables selecting insensitive variables (Trucano et al., 2006), identifying the key features and patterns in the data (Behrens, 1997; Gelman, 2004). One of the most comprehensive techniques used to reduce the dimension of the variables is the binomial logistic regression and the multinomial logistic analysis. The binomial logistic regression is used to estimate a dichotomous dependent variable, whereas the multinomial logistic analysis is suitable for regression analysis with multinomial responses. Furthermore, select variables from other similar works and identify the most widely used, is another technique that can be performed (Rocha, 2012)

Variables conversion

Different normalization techniques have been used to transform data into a range of fixed values, such as fuzzy logic (Jiang and Eastman, 2000; Zadeh, 1965), multi-label classification (Omrani et al., 2017), Z-score (Altman, 1968), and min-max (Jain et al., 2005). Fuzzy logic is one of the most widely used. Studies based on fuzzy logic have been applied in several scientific areas such as robotics, computer modelling, engineering and geographical studies, e.g., Asakereh et al. (2014), Kainz (2001), and Guesgen and Hertzberg (2001). The fuzzy distance operators available in GIS environment define the shortest distance at each grid intersection to a set of target places. Fuzzy distance makes the data more accurate and is more appropriate for dealing with real-world problems. In fuzzy logic, there are three basic operations: union, intersection, and complement (Mizumoto and Tanaka, 1981) (Fig. 2.1).

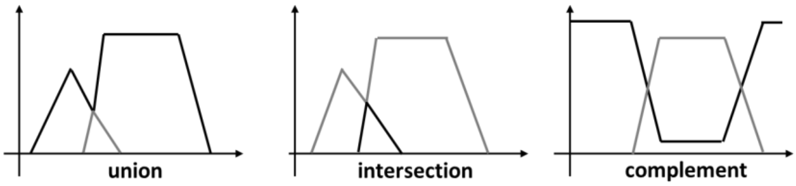

Figure 2.1 – Fuzzy operations.

The fuzzy distance as a measure of fuzzy numbers in Euclidean space (Al-Ahmadi et al., 2009) estimates the shortest distance in the plane (Danielsson, 1980), which corresponds to the distance between point *x* and point *y* (Fig. 2.2).

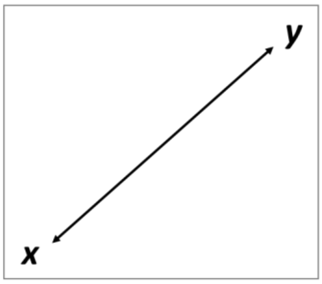

Figure 2.2 – Euclidean distance.

In fuzzy logic, each location has a degree, e.g., between 0 and 1 (Fisher, 2000), and must have x, y locations, X_a, Y_a and X_b, Y_b. The distance between them can be expressed by the Pythagorean equation, which reveals the distance between two locations in a single value. Once, one of the two sites is represented as a fuzzy object, the sites need to be modelled as a fuzzy number. Another type of data normalisation is Boolean, in which only two values are considered - true or false (e.g., 0 or 1) (Fig. 2.3).

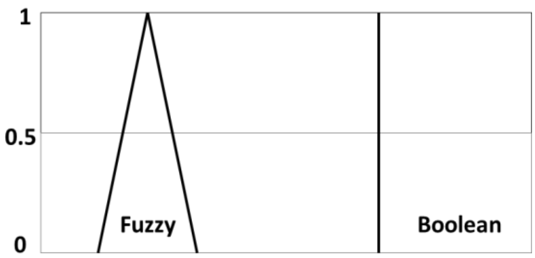

Figure 2.3 – Fuzzy and Boolean methods.

Processing, assessing and validation

Calibration and validation are critical processes to land-use models. Calibration is the process to adjust the parameters to improve the model outcomes, reducing divergences between the observed and simulated results, whereas validation is the process for evaluating the quality of the outcome, verifying the tolerable range of accuracy (Rykiel, 1996). The efficiency of these techniques is dependent on the available data.

LUCC are frequently calibrated to reproduce known past land-use patterns (Silva and Clarke, 2002). When enough data is available, the model is validated separately (Batty and Torrens, 2005; Kok et al., 2001), which means that the data used for validation is not used for calibration. A separate calibration can identify biased or overfitting models (Radosavljevic and Anderson, 2014). The accuracy assessment can be evaluated between two-time periods (t_1 and t_2). The last time-period can be predicted and compared to a reference map. If the reference map and the predicted map (for the same period) reveal a high degree of similarity, it will be demonstrated that the model will be successful in predicting the LUCC in the future (Mishra et al., 2014; Pontius et al., 2004).

Two different kinds of data sets must be used for calibration and evaluation procedures. Separation of time and space are one of the techniques used to calibrate data from the validation data set. The calibration method performs the statistical regression on the change quantity between point t_0 and t_1. The fixed limits and the regression relationship can be used to extrapolate the changes between point t_1 and t_2. A validation technique establishes the predicted map of time t_2 to the reference map of time t_2. The difference between the calibration and validation procedures can help to ensure that the model is not over-fitted (Pontius et al., 2004). Validation of LUCC models is implemented both qualitatively and quantitatively. Qualitative validation comprises the assessment of plausibility (An et al., 2005), clarity and intelligibility in the model (Acevedo et al., 2008). Quantitative validation connects models results in real-world data or results of other models (Acevedo et al., 2008; Parker et al., 2003).

Due to the uncertainty and complexity of LUCC models, different techniques to validate models are used. Visual interpretation is one of these techniques, providing a better evaluation of model performance. However, this technique has as a disadvantage the fact of visual interpretation is sometimes subjective, which means that a good result for one specialist could be a bad result to another (Butt et al., 2015; Puig et al., 2001). In this way, Brown et al. (2005) propose the concept of predictive accuracy (aggregate similarity) and process accuracy (spatial similarity). Predictive accuracy corresponds to the assess whether LUCC is located (van Vliet et al., 2013) (e.g., fuzzy set and multi-resolution approach), while process accuracy refers to measures whether LUCC is simulated realistically (Brown et al., 2005) (e.g., landscape metrics and fractal dimension of patches). There are other methods employed such as conversion matrix e.g., Li and Yeh (2001), Receiver Operating Characteristic (ROC) e.g., Hajian-Tilaki (2013), landscape metrics and spatial statistics e.g., Ménard and Marceau (2007), fuzzy polygon matching techniques e.g., White (2006), and kappa simulation statistics e.g., van Vliet, Bregt, and Hagen-Zanker (2011) and Hasbani et al. (2011). The kappa statistic (or kappa coefficient) is the most widely used for this purpose. Kappa measures inter-rater agreement between categorical variables x and y, which evaluate the prediction performance of classifiers (Cohen, 1960). A Kappa of 0 indicates agreement equal to chance, while a kappa of 1 indicates a perfect agreement (Viera and Garrett, 2005).

Although there are several techniques to validate LUCC models some studies have demonstrated that some models cannot be validated. Konikow and Bredehoeft (1992) and Oreskes et al. (1994) explained some arguments. The main issues are the following: i) it is not possible to prove the veracity of any model, except for a closed system; ii) the relation between the scale of the process and the scale of the representation is frequently unidentified; iii) the inevitable existence of errors in parameterization during a simulation; and iv) errors might raise within a big-time span of the validation. Thus, validation is an open-finished challenge without an ending (Aumann, 2007). Furthermore, the using a specific validation method does not mean that this could be the best one, and it is not necessarily an indication of the quality of the accuracy assessment of land-use models (Manson, 2007). Other studies have shown that LUCC is uncertain because human decisions that drive LUCC are infrequently deterministic (Manson, 2007), and because LUCC is caused by biophysical, demographic, and socioeconomic drivers that are mutually influential (Lambin et al., 2001). Moreover, the uncertainty is also expressed in many land-use models, especially those that comprise stochastic algorithms to simulate LUCC (Koomen et al., 2007).

3. Integrating complexity science and Geography in LUCC modelling

As an emerging approach complexity science is the study of a system to understand and predict the behaviours of complex systems. The original Latin word of complexity (*complexus*) has the meaning entwined and twisted together, which may be perceived as something that has two or more elements, and that cannot be analysed separately. Complexity science has fascinated in the last decades a large number of fields such as natural and social sciences.

The engagement between Geography and complexity science agenda has increasingly aroused interest. New knowledge has been established to explore interconnected relationships, unpredictability, multi-dimension, multi-scale and multi-time, and non-linear thinking.

3.1 Complexity theory: evolution, main principles and models

Complexity theory describes how the local interactions between individuals in a system lead to emerging patterns over time (Holland, 1992). René Descartes in century XVII (1596-1650) defended that "nothing comes out of nothing". This quote can in a simplistic way describes how complexity science has been developed. Does not exist a single definition of complex system and there is no consensus about it (Newman, 2009), partially due complex system theory itself became recognised correctly only in the 1990s (Waldrop, 1992). However, it is agreed that complexity science corresponds to a system with interactions in a set of entities, processes, and agents (Heppenstall et al., 2016; Mitchell and Newman, 2002), through an extensive network with no central control (Mitchell, 2006). Local interactions between agents and the environment can result in unexpected and unpredictable behaviours at the global level, in a new bottom-up approach (Massotte, 1996). These local or global interactions can have positive and negative responses that can influence the system state (Bennett and McGinnis, 2008).

Furthermore, complex systems consider that connexions and interdependencies are challenging to describe, to predict and to manage (Magee and de Weck, 2004), and they are the result of collective behaviours. Complex systems are more than the sum of individual actions (Newman, 2009). For a system to be called complex, needs to have their components self-organised, and less dependent on environmental actions (Cotsaftis, 2009). Complexity science explores the dynamic systems in a broad and multi-disciplinary context. Since the first approaches, complexity science has spread from several disciplines, and they have contributed to the understanding of complexity science. Following we present some of these fields and its principal object of study:

- Catastrophe theory – studies systems presenting unexpected discontinuous changes (Thom, 1977);
- Chaos theory – studies the stability of procedures in response to changes of scale (Feigenbaum, 1978; Li and Yorke, 1975; Lorenz, 1963);
- Cybernetics (by Norbert Wiener in cybernetics mathematics; William Ashby in cybernetics of mind; and by Claude Shannon in information theory) (Heylighen, 2007) – investigates the regulation of process as complex systems;
- Fractal geometry – describes and analyse irregularity (Mandelbrot, 1982);
- Artificial intelligence – model activities and information lows as network structures (Spector, 2006);
- Genetic algorithm – studies the answers for both constrained and unconstrained optimisation problems (Holland, 1992);
- Ecological systems theory – studies ecological issues at different levels (Villamagna et al., 2013);
- Geographical complexity – studies the geographical issues related to the complex systems (Barabási et al., 2011; Batty, 2005; O'Sullivan et al., 2006; Thrift, 1999; Urry, 2010);
- Big data/ data science – analyse and manipulate data and subjects' behaviour (Börner and Scharnhorst, 2009; Marres, 2017; Stonebraker, 1986), and
- Agent-based modelling – studies the interactions between people, things, places, and time (Axelrod, 1997; Epstein and Axtell, 1997; Epstein, 2002; Ilbert, 2007; Schelling, 1978; Squazzoni, 2012).

Next, we illustrated in Figure 2.4 the emergence of each scientific field in the corresponding decade (directly or indirectly studied by land-use science), since its beginning (in the 1940´s) until the present moment (2020´s) (Castellani, 2018).

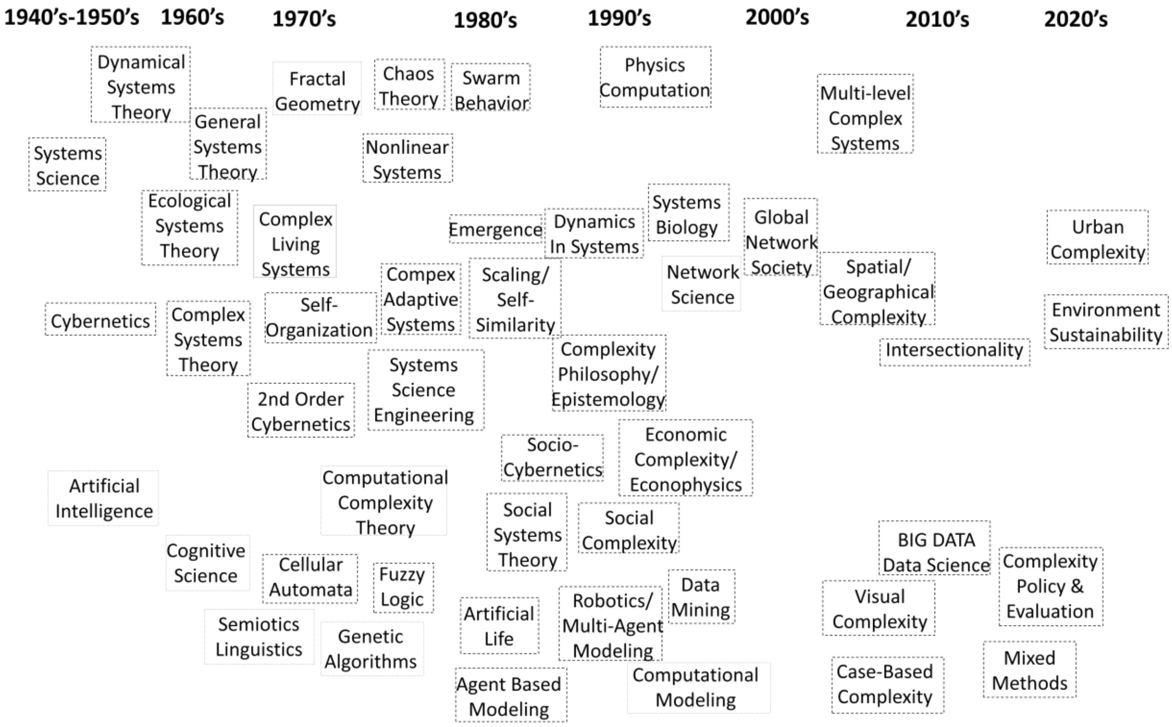

Figure 2.4 – The history of complexity science (adapted from Castellani, 2018).

In the following, we described three principles of the scientific fields that gave origin to the complexity science, namely the self-organisation, nonlinearity, and order and chaos:

i) Self-organisation is an essential concept in complexity science (Heylighen, 2008). In self-organisation, the interactions inside the system, lead to the spontaneous emergence of an intelligible spatial structure without exterior coordination, where there is no hierarchy of command and control, neither internal or external agents that monitor the process (Heylighen, 2008). This concept is the spontaneous emergence of a global structure of local interactions (Bonabeau et al., 1997; Heylighen, 2008).

ii) Nonlinearity is a method of continuous and discontinuous change, diverging, according to speed, intensity, and effect. In nonlinearity, the cause-effect relation is disproportional, and the systems may change in structure and function. In non-linearity, there is no possibility to "*add any two solutions to the equations that describe it and obtain another, and multiply any solution by any factor and obtain another*" (Ladyman et al., 2011).

iii) Order and chaos dynamic is part of the system that competes or cooperates with another system (Rickles et al., 2007). Chaos dynamic is related to unpredictable behaviour in a system

(Robb and Jimmy Gandhi, 2016). In the emergence, agents interact randomly with other agents, rather than being planned or controlled. This emergence has two types: weak and strong. The type weak is linear and can be homogeneous, independent, additative and synchronous. In another way, the type strong is nonlinear and is heterogeneous, interdependent, non-additative and asynchronous (Chalmers, 2006; Lichtenstein and Plowman, 2009).

The complex systems evolution often comprises disconnected time-scales. The disconnection or transition is the consequence of an aggregation of techniques of changes, since collective behaviours and relations, physical, economic, or social configurations, cause irreversible changes in a system (Vasileiadou and Safarzyńska, 2010). Rotmans et al. (2001) identified four stages of stability transition: pre-development, take-off, breakthrough or acceleration, and stabilisation (Fig. 2.5).

1) In pre-development, indicators change only slightly, which does not exist a dynamic of equilibrium;

2) In the take-off and acceleration stage, indicators change with growing speed, and the system starts to break;

3) In the breakthrough or acceleration phase, the system changes structurally (Loorbach and Rotmans, 2006); and

4) In the stabilisation stage, the speed of social change declines and a new dynamic equilibrium is achieved.

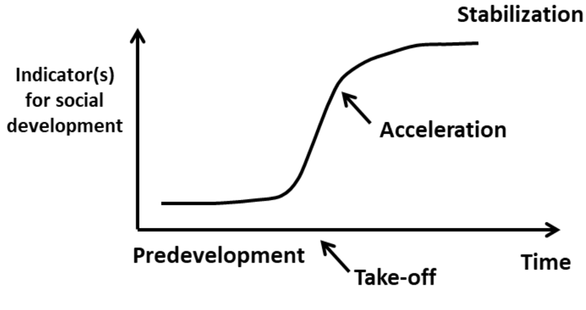

Figure 2.5 – Stages of transition (adapted from Rotmans et al. 2001).

These multi-stages provide a straightforward interpretation of what will occur throughout a transition process. The conceptual theory proposes a cyclic pattern, and a stabilisation stage, and can be the predevelopment stage for the next development stage.

Complex systems studies are increasingly used in natural and social sciences (Ladyman et al., 2011), and provides a powerful tool to capture evidence about the world (Lempert, 2002). More recently complexity science has been studied in new fields of knowledge such as urban complexity (Bertolini, 2007; Bettencourt et al., 2007), and policy and evaluation (Befani, 2013; Gerrits and Merks, 2017; Geyer, 2003; Johnson, 2015; Mitleton-kelly, 2003; Morcol, 2012; Penn et al., 2013; Room, 2016; Silva and de Roo, 2010).

In urban complexity have been studied urban form and energy (Salat and Bourdic, 2012), spatial strategies (Healey, 2006), food, energy, and water security (Romero-Lankao et al., 2017), and the analysis of economic, demographic and urban morphology (Batty, 2008). Otherwise, policy and evaluation have been related to the understanding of collective decision-making.

Whereas complexity science is in its early steps, it has had an impact on the development of computer models that can address simulation and modelling techniques. A model experiment can represent the application of simulation and modelling techniques in a complex system approach. Computer simulations have been considered to solve complex problems (Vangheluwe, 2001) and can integrate empirical data, entities, relations among objects; and a period. Simulations reproduce experimentally-observed real systems (real world) and can be divided into space and time (Fig. 2.6).

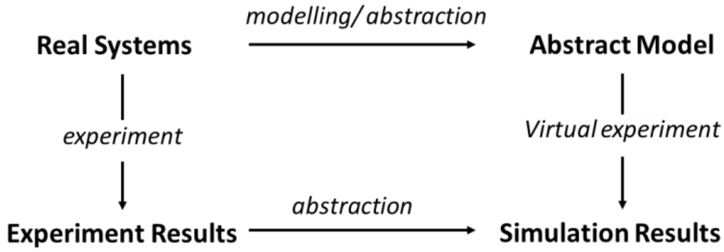

Figure 2.6 – Real systems vs abstract model.

A model is an abstraction of the world. Mathematical modelling has become an essential tool for the analysis of spatial phenomena, e.g., Batty (2005), and Encinas et al. (2007), suggesting a proper language to define complex behaviours (Marsan, 2009).

There are three different types of mathematical modelling approaches to describe these dynamics: (1) deterministic; (2) stochastic; and (3) hybrid:

(1) Deterministic: In deterministic models, the material properties are well known. The output of the model is entirely determined by the parameter values and the initial conditions, displayed by deterministic rate equations. A deterministic model can be stretched to account for the spatial organisation and has been effectively used to analyse reaction process (Batty and Longley, 1986; Musa et al., 2017).

(2) Stochastic: Stochastic models have intrinsic randomness. The set of parameter values and initial conditions will lead to an ensemble of different outputs.

(3) Hybrid: The hybrid model is a combination of both deterministic and stochastic models. Shanthikumar and Sargent (1983) suggested that hybrid models are used in analysis, optimisation, synthesis, gaining and in the comparison of alternative systems. Hybrid models avoid the difficulties associated with an only discrete or only continuous system representation.

The increasing use of complex model simulations is related to the price (low cost), speed (faster) and reproducibility (Iba, 2013). In the social science context, CA-Markov, ANN, and ABM have been widely used to describe and understand the dynamics of the system, to predict future behaviours. They have the advantage to remain simple but incorporating complex behaviours. The coupled approach of Geography and complex science in the study of LUCC modelling allow to describe, to understand, and to identify connexions among space-time patterns at multiple scales, relating interactions and nonlinearity between different factors.

LUCC models in Geography

Geographic modelling explain and predict geographical phenomena (Worboys, 2005). Theories and methods adopted from a new perspective of spatial simulation modelling have been used. The geographic models incorporate an accurate representation of geographic phenomena. They integrate an object-based and spatially-explicit approach linked to the complex systems dynamics (Mekni et al., 2012). They allow to better understand the spatiotemporal phenomena (Anderson and Dragicevic, 2016; Openshaw and Alvanides, 1999), through modelling human behaviours (Loewenstein and Lerner, 2003).

Geospatial modelling represents an advance of geographic information science (Batty et al., 2012) which has been contributed to an efficient way to reflect about new space perceptions (Blaschke and Merschdorf, 2014), answering the questions how? why? when? where? and what?. They create spatial knowledge and can be used as a support for spatial decision-making (Gounaridis et al., 2019; Lestrelin et al., 2017).

Predicting and assessing future LUCC trajectories allow to identify their causes and consequences (Verburg et al., 2004). The complexity of land-use systems involve a multidisciplinary evaluation (Agarwal et al., 2002), integrating a broad range of data such as biophysical, demographic, and socioeconomic variables (Houet et al., 2014; Silva and Wu, 2012; Wang and Li, 2011).

Currently there are a variety of LUCC models based on different empirical techniques, such CA (Li and Li, 2015), ANN (Morgado et al., 2014), ABM (Bert et al., 2011), multiple regressions, equation-based models (Parunak et al., 1998), system models (Nazemi and Wheater, 2015), statistical techniques (Lesschen et al., 2005), expert models (Landis, 1997), evolutionary models (Thrall et al., 2011), economic principles (Ward, 1961), spatial interaction (Silveira and Dentinho, 2010), evolutionary algorithms (Seixas and Nunes, 2007), genetic algorithms (Matthews et al., 2000), optimization techniques (Meyer et al., 2009), hybrid models (Berry et al., 1996), and microsimulation (Moeckel et al., 2003). One of the most widely used approaches in LUCC simulation are CA, ANN and ABM (Li and Yeh, 2000; Stevens and Dragic, 2006; Yüzer, 2004). They have been used to simulate LUCC dynamics, identifying its driving forces (Houet et al., 2010), and to capture the behaviour of individuals (more specifically in the case of the ABM).

3.2 Cellular Automata

CA has become the prominent modelling approach connected to complex system theory. The mathematicians Stanislaw Ulam and John von Neumann in the 1940s developed the CA method to investigate the behaviours of complex systems (Popovici and Popovici, 2002; Vangheluwe, 2001; White and Engelen, 1993). CA have identical automata cells organised on lattice points in a *D*-dimensional discrete space, in which the temporal change is expressed by: $S_t+1(x)=F(S_t(x+X_o)S_t(x+x1),\ldots,S_t(x+X_{n-1}))$, in which $S_t(x)$ corresponds to the state, in each automaton is located at (x) in the time (t); F corresponds to the state-transition function; $N=\{x_o,x_1,\ldots,X_{n-1}\}$ to the neighbourhood; and S_t to the function that identifies locations.

Traditionally CA is designed by five main elements: cell space; time step; cell states; cell neighbourhood; and transition rules (Jiao and Boerboom, 2006).

Cell space (lattice) can be square (de Almeida et al., 2003), hexagonal e.g., Encinas et al. (2007) and Bays (1994), triangular e.g., Dyer and Rosenfeld (1981), or irregular e.g., Baran et al. (2011) (Fig. 2.7).

Figure 2.7 – Cell space: square (a), hexagonal (b), triangular (c), and irregular cell (d).

Time step corresponds to the dynamics of each cell progress step by step (Wolfram, 1984) and identifies the temporal dimension. Most of the CA examples are synchronously (Regnault, 2006). In synchronous mode, the numbers of cells change at once – in each time step. On the other hand, in the asynchronous mode for each time step, just one updating is executed to one randomly chosen cell (Schönfisch and De Roos, 1999).

Cell state defines the attributes in the system. Each cell can take just one state at every time steps. Cell states are represented by at least for two categorical states. In urban modelling, states can be characterised by urbanised or not urbanised (White et al., 2015). Every time the system is updated as a result of the evaluation of the transition rules in the interactive neighbourhood, and the state of each cell will be updated at any change (or the state will be maintained).

In the cell's neighbourhood, each cell is influenced by the nearest cell (Ilachinski, 1987; Schiff, 2011). The neighbourhoods may have adjacent cell clusters defining distances to an individual automaton. The neighbourhood patterns are on Moore - 5x5 cells, Moore - 3x3 cells or Von Neumann (5 cells) method.

Transition rules define how the state of one cell changes. Classic CA transition rules are deterministic. In some investigations, transition rules are modified into stochastic methods and fuzzy logic (Wu, 1998).

CA became more common and popular when John Conway, in 1970, designed the Game of Life (Huang et al., 2009), the most popular 2-D binary CA. In this model, a finite space is divided into equal cells. The rules of the game are simple: on a grid, a set of rules is applied to the contents of each cell at each iteration of the automaton. It is represented by two states: ‘alive’ or ‘dead’ with an eight-cell Moore neighbourhood (White et al. 2015).

A cell can “live” when a cell is “dead” at time t will be alive at time $t + 1$ (if three of its neighbours were alive at time t). In another hand, a cell can “dead” in two ways: overcrowding and exposure. The cell can die of overcrowding if more than three cells live and can die of exposure if there are less than two (Salen and Zimmerman, 2004). A cell can survive from the time (t) to time (t) + 1 if two or three of its neighbours are alive at the time (t) (Gardner, 1970) (Fig 2.8).

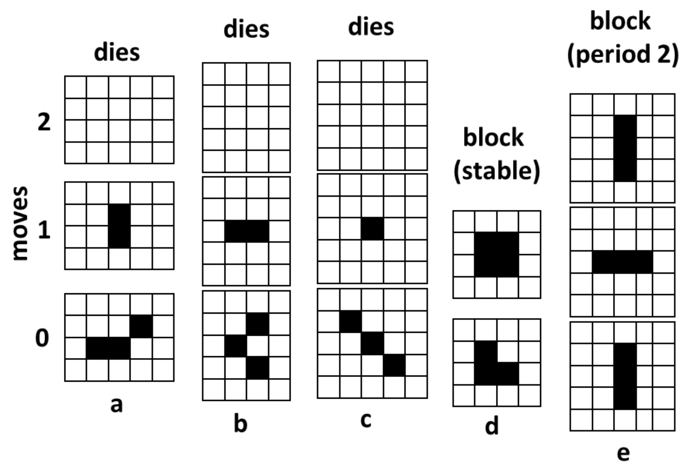

Figure 2.8 – Transition process of the game of life (adapted from Gardner, 1970).

A ”lived” cell with 2 or 3 “lived” neighbouring cells will live for the next step (a0 to a1). Each cell with 4 or more “dead” neighbour’s cells will die (will be removed) for the next step (c1 to c2). Each empty (“dead”) cell adjacent to 3 neighbours is a “birth” cell, and it will turn into a “lived” cell in the next step (b0 to b1).

Once the interaction begins, the transition rules are initially applied to “lived” cells to recognise whether they will be survivals (or not) for the next interaction. Next, all cells will be verified. If they meet the “dead” transition rule, they must convert or maintain the status for the following interactions. Lastly, entirely “dead” cells are analysed to identify where “births” will happen. Once these steps have been verified, the cells will modify or maintain their status, and then they will move to the next interaction. A similar practice is reiterated to produce succeeding generations (steps) until all cells are in a stable state (d0 to d1) or a blinkered state (e0 to e1 to e2) (Baran et al., 2011; White and Engelen, 1993; Wolfram, 1984).

CA are one of the most widely used methods (Macal and North, 2010). It is a powerful method for studying complex systems and exploring principles of system evolution and self-organisation (Mitchell, 1998). The simplicity of CA can create spatial-temporal configurations of great complexity over a restricted set of simple rules (Mitchell, 1998; Silva, 2011). CA are arranged in a regular spatial grid characterised by local interactions (Shalizi and Micheli-Tzanakou, 2006), updated according to their neighbours.

In 1907, Andrei Markov, a Russian mathematician, initiated the investigation of a new stochastic model. In this method, designed Markov chain, the results of a given test can affect the results of the following experiment. Markov Chain is represented by a set of random variables (Diaconis, 2009), and has a transition probability matrix expressed by $t_1 < t_2 ... t_n < t_{n+1}$ where t_n corresponds to present time, t_{n+1} to a point in the future, and $t_1, t_2 ..., t_{n-1}$ to several locations in the past (Basharin et al., 2004; Levin et al., 2009).

If the Markov chain has a restricted number of states, it is expressed by the following transition probability matrix (2.1):

$$\begin{pmatrix} P_{1,1} & P_{1,2} & ....P_{1,n} \\ P_{2,1} & P_{2,2} & ....P_{2,n} \\ ... & ... & ... \\ P_{n,1} & P_{n,2} & ....P_{n,n} \end{pmatrix} \tag{2.1}$$

Markov chain outcomes are dependent on the present state and enable to divide between discrete and continuous time (Taylor and Karlin, 1998).

CA for LUCC geospatial modelling

Geospatial modelling is widely used in CA to model processes in space and time. Following successive theoretical explorations and structure improvements, CA has become a well-established method for modelling LUCC in recent decades and has been widely used since it was introduced by Tobler (1979). CA has the ability to simulate dynamic development from a bottom-up perspective (Liu et al., 2008a), based on complex spatial forms (e.g. Agarwal et al. 2002; de Almeida et al. 2003; de Kok et al. 2001; Li and Yeh 2002; Singh 2003; Wang and Li 2011). CA-based on Markov chains is increasingly employed in LUCC (Dezhkam et al., 2017; Sang et al., 2011) incorporating the relationships between land use and driving forces that explains the LUCC in different periods. Some studies have been carried out regarding the usability of CA for LUCC simulation at different spatial resolutions. Large spatial resolutions make difficult the identification of detailed land-use transitions. Otherwise, CA models developed at small spatial resolutions have the advantage of a detailed resolution data, facilitating the identification of land use relationships, which is relevant to suggest and implement local, and sustainable environmental policies (Pan et al., 2010; Stanilov and Batty, 2011). Small spatial resolutions are one of the most critical processes for land use planning and decision making (Antrop, 2004; Antrop and Van Eetvelde, 2000; Meeus and Gulinck, 2008; White and Engelen, 2000). Planners and decision-makers need to obtain high-resolution information on LUCC over time. However, there are few studies based on land use at small resolutions. It is mainly related to data availability (Bounfour and Lambin, 1999; Xie et al., 2007). Some examples of CA-LUCC models are presented below in Table 2.2.

Table 2.2 – LUCC models based on CA.

Method	Model	Description	Source
CA	**MOLAND**	Provides a spatial planning tool used to evaluate, to monitor, and to model the urban development at the regional level.	(Shahumyan et al., 2014)
	SLEUTH	Designed with predefined rules. SLEUTH uses four types of urban LUCC: spontaneous growth; new spreading centre growth; edge growth; and road-influenced growth.	(Silva and Clarke, 2002)
	RIKS	It is developed at two scales. Macro-level: create LUCC based on socio-economic factors. Micro-level: allocate the cells to different land-use types.	(Engelen, 1988)

3.3 Artificial Neural Network

ANN is a variant of the machine learning system inspired by the human brain neurons structure (Ahmad et al., 2017). ANN is an adaptive system that changes through the training time (Devi et al., 2013). The basic unit of computation in an ANN is the neuron (Monge and Crespo, 2017), which accepts inputs from other nodes with a specific weight. The output is a non-linear function, called activation function (Mishra et al., 2017), and performs a fixed mathematical operation (e.g., sigmoid, linear activation, piecewise linear activation, tangent hyperbolic, and threshold function) (Zamanlooy and Mirhassani, 2014). Each activation function is selected depending on the nature of the problem to be explained by the network.

An ANN is categorised by three different types of nodes (Jain and Chakrawarty, 2017):

(i) input layer - connects with the external environment;

(ii) hidden - is the intermediate layer between input and output, and

(iii) the output layer - shows the pattern to the external environment.

The learning methods in ANN are classified into supervised, unsupervised, and reinforced learning. In the supervised learning a segment of the training data performances as a teacher to the algorithm to fix the model; in unsupervised learning, a teacher is not present during the learning process; and in the reinforced learning a teacher is present but the expected output is not present (Carpenter and Grossberg, 1994).

In the training process, weights are adjusted according to different algorithms. They are the gradient descent (with five different types) and the resilient backpropagation (Leema et al., 2016). The most widely used algorithm is the backpropagation which spreads errors back during the training, e.g., Fan et al. (2018) and Anifah et al. (2017).

There are several types of neural networks such as feedback (Djarfour et al., 2008), feed-forward (Sawhney and Jeyasurya, 2006), multilayer perceptron (Sy, 2006), convolutional neural network (Liang and Hu, 2015), recursive neural network (Baldi and Pollastri, 2003), recurrent neural network (Cheng and Wang, 2007), long short-term memory (Hochreiter and Schmidhuber, 1997), sequence-to-sequence models (Doetsch et al., 2017), shallow neural networks (Soltanolkotabi et al., 2017), and Radial Basis Function (Orr, 1996). One of the most widely used is the feed-forward and Radial Basis Function. The feed-forward neural network was the first category of ANN created. Its data flows in one direction and have multiple nodes (or neurons) organised in layers. The nodes from adjacent layers have connections among them, in which no cycles in the network are presented. This network can have a single layer (does not have hidden layers) and a multi-layer perceptron (has one or more hidden layers) (Minemoto et al., 2017). The Radial basis function is a feed-forward network using a supervised training algorithm and organised with a single hidden layer of units (Kayri, 2015).

ANN has been widely used to identify non-linear patterns. ANN is an emerged method (Ebrahimi et al., 2017; Mayoraz et al., 1996; Pijanowski et al., 2002) used for quantitative data modelling such as land use simulation (Morgado et al., 2014), climate forecasting, data mining and financial applications for knowledge induction and decision support. The ANNs share the learning ability of humans and the principles of the human brain into the computer environment.

The application of ANN has increased over the last few years due to advances in computer performance (Khan et al., 2013), and the increasing availability of ANN packages (Khan et al., 2013).

ANN for LUCC geospatial modelling

ANN models have been used to detect and to monitor LUCC (Islam et al., 2018; Morgado et al., 2014; Pijanowski et al., 2002). ANNs use a machine similar to human behaviour (Bersini, 2006) to quantify and model complex behaviours and patterns (Abdolrazzaghi et al., 2018; Aiolli et al., 2018). ANN is based on a machine-learning algorithm to model complex behaviours and patterns (Ebrahimi et al., 2017; Mayoraz et al., 1996; Pijanowski et al., 2002) and has been used to address prediction problems in many fields of scientific research such as energy applications in buildings (Kalogirou, 2015), medical issues (Liu et al., 2013), and land use simulation (Morgado et al., 2014).

The use of the ANN technology has increased over the last few years due to advances in computer performance (Khan et al., 2013), and the availability of ANN packages (Khan et al., 2013). Some advantages of applying this algorithm are its data-driven and self-adaptive capabilities, and the use of universal functional approximations. These do not require initial hypotheses on the data.

The popularity of ANNs in the social sciences over the last decades have been due to the capability to learn complex phenomena (Garson, 1998). This learning takes place over probabilistic and logical functions (Specht, 1990), and its aptitude arises from the interaction between its neurons (Schneider et al., 2018). From the types of ANN, Multilayer perceptron (ANN-MLP) have been widely applied in social sciences (Alizadeh et al., 2018; Gazder and Ratrout, 2015; Tamas et al., 2014). In LUCC, ANNs have as main advantage to integrate several explanatory variables that are based on empirical data (Chen et al., 2009). It consists of three steps: (i) classification through a decision-tree approach; (ii) transition of land use class; and

(iii) modelling the future LUCC. Some examples of ANN-LUCC models are presented below in Table 2.3.

Table 2.3 – LUCC models based on ANN.

Method	Model	Description	Source
ANN	GIS-ANN Web - SECOA	It allows stakeholders to measure LUCC according to different scenarios.	(Morgado et al., 2014)
	Land Transformation Model	Land use predicting model and identify the spatial and temporal patterns of LUCC and its driving forces.	(Pijanowski et al., 2002)

3.4 Agent-based model

ABM has emerged in recent years, with its origins in artificial intelligence (AI) (Moulin and Chaib-Draa, 1996). It enables to reproduce human actions such as cognition, communication, and learning (Conte and Paolucci, 2014). Although CA and ANN modelling is centred on how simple rules lead to transitions, ABM is centred on how interactions through computer-encoded agents express the decision-making behaviours. ABM is one of the most capable modelling methods to assess complexity science theory (Macal and North, 2009; Jokar Arsanjani et al., 2013; Mitchell and Newman, 2002), adaptive systems (Holland, 1995), and artificial life (Langton, 1989). Inspired and reinforced by increasing computational power, ABM as part of complexity science and intelligent systems (Chen, 2012; Conte and Paolucci, 2014) is considered an advanced approach to simulate Real-World Systems (Batty et al., 2012). ABM integrates agents that have control over its actions to achieve predefined objectives (Banos, 2010; Wooldridge, 1997), according to the following key features (Benenson and Torrens, 2006):

(1) autonomy: the agents are independent and autonomous, and they can swap information between other agents (Castle and Crooks, 2006; Parker et al., 2003);
(2) heterogeneity: the agents have connections with other agents, acting as a group, in a bottom-up approach (Brown et al., 2008);
(3) mobility: the agents can move in environmental space, interacting with each other, and sharing knowledge;

(4) adaptability and learning: the agents are flexible to create complex adaptive systems (Holland, 1995), which can change its current state, and acquiring memory and learning (Smith et al., 2009); and

(5) activity: the agents are independent in simulation. They are (i) pro-active: with goals according to their behaviours; (ii) reactive: they can be developed to have consciousness about their surroundings; (iii) bounded rationality; (iv) they are able to optimise information, and to have analytical capabilities (Parker et al., 2003); and (v) interactive and communicative: they communicate with each other.

An ABM is designed according to different rules, such as mathematical or logical, explaining how, and who they are related to (Bandini et al., 2009; Gilbert, 2007). Agents can interact with each other by a cognitive model, establishing connections between their autonomous objectives, spatial environment (Luck et al., 2005), and they can be developed at multiple scales (Eames et al., 2014). Also, agents establish with each other coordination, communication, cooperation, competition and negotiation procedures (Jennings, 2000; Moulin and Chaib-Draa, 1996).

ABM measure collective behaviours, and it is particularly useful when agents interact in a non-random manner. Agents are essential to test cognitive decision-making processes and to test the unpredictability in human behaviour related to the emotional responses (Crooks, 2009) (Fig. 2.9).

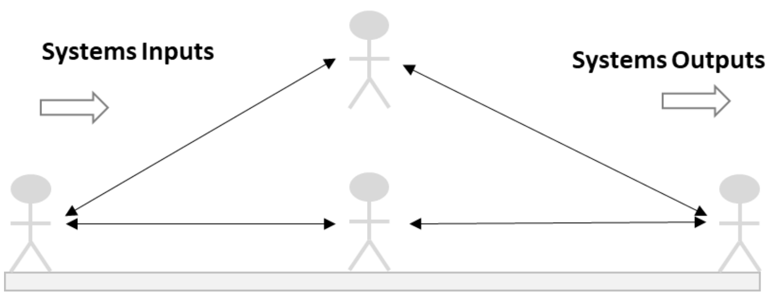

Figure 2.9 – ABM representation.

ABM is applied as experimental media to perform and to monitor simulations, as a support analysis of decentralised decision-makers, local-global interactions, self-organisation, emergence, and effects of heterogeneity in the simulated system (Bandini et al., 2009). In an exploratory laboratory experiment, agents' attributes and behaviours can be changed, and the impacts visualised according to the run of multiple simulations (Evans et al., 2006).

ABM in the context of social sciences helps to understand what led to the decision-making in human activities (Valbuena et al., 2010a). It helps to analyse the agent's social and cognitive capabilities, their level of experience, preferences, and motivations (Conte and Paolucci, 2014). ABM represents a new paradigm for simulation agent's interactions (Barton, 2014).

Until very recently, modelling techniques were restricted to examine the relationship between spatial elements. ABM introduces a non-spatial component to simulate agents' behaviours, and their interactions in the environment (how agents influence and how agents are influenced by the space) supported by computer simulation modelling (Macal and North, 2009). ABM is being applied to several scientific areas. Thomas Schelling in 1971 developed one of the earliest ABM applied to social sciences to explain and to evaluate racial segregation in American cities. According to Allen (1997), Schelling model influenced many authors later, namely due to the outcomes, model simplicity, and the model robustness.

In recent years another ABMs have been applied in areas such as agriculture (Leyk et al., 2009), ecology (Grosman et al., 2011), environmental planning and policy (Zellner, 2008), and social networks (Mason et al., 2008).

Theoretical models are implemented through computer simulations techniques (Gilbert and Terna, 2000) and developed in different steps. According to Macal and North (2009), the decision to establish ABM implies enumerating a set of seven questions: 1. which problem should be explained by the model? 2. what are the agents in the model, with their behaviours, attributes, and dynamics? 3. what is the agent environment? 4. which actions are taken by the agents? 5. how does the agent interact with other agents? 6. where the agent's behaviour data come from? and 7. how to validate the model?

Castle and Crooks (2006) recognised three main advantages of using ABMs: (i) emergent phenomena; (ii) human's perception of real-world events; and (iii) agents who are flexible to learn from the environment. ABMs promise to have far-reaching effects in several areas to support decision-makers and researchers.

ABM for LUCC geospatial modelling

ABM offers an approach for evaluating the spatiotemporal relationships in LUCC through modelling its mechanisms, representing human decision-making, and using autonomous agents (Bonabeau, 2002) to describe different perceptions and behaviours (Bandini et al., 2009).

ABMs and GIS together can better understand spatial characteristics and complex interactions. The firsts models coupling ABM and GIS were in the study of pedestrian behaviours (Batty et al., 2003) and urban dynamics (Portugali et al., 1997; Sanders et al., 1997). SIMPOP in 1996 was the first ABM applied in Geography. SIMPOP analyses the urban settlements transitions at different times and scales (Bura et al., 1996; Pumain, 2006; Sanders et al., 1997).

In the last years, ABM is increasingly employed to understand LUCC in agroecosystems level, model human-environment interactions, modelling urban growth patterns (Chen, 2012), and traffic patterns. A comprehensive review of ABM-LUCC is explored by Parker et al. (2003) and Bosquet and Le Page (2004). The strength of ABM for LUCC is on understanding the emerging patterns that arise from the interactions between agents and space.

Although the attractiveness of ABM only in the last two decades have been recognised in the number of applications for simulating LUCC. Examples comprise the use of ABM for simulating the dynamics of urban modelling (Gilbert and Conte, 1995), and for simulating forest-agriculture transitions (Castella et al., 2005; Deadman et al., 2004). These applications allow an understanding of how individual interactions can produce large-scale outcomes in emerging patterns dynamics (Chen, 2012). Some examples of ABM-LUCC models are presented below in Table 2.4.

Table 2.4 – LUCC models based on ABM.

Method	Model	Description	Source
ABM	**PUMA**	It simulates LUCC based on a land conversion model and household model.	(Ettema et al., 2007)
	ILUMASS	It was developed to run at microscopy level, simulating LUCC, transportation, and environmental dynamics.	(Wagner and Wegener, 2007)
	RAMBLAS	It simulates the impacts of LUCC, and transportation planning policies.	(Veldhuisen et al., 2000)

	Desakota	It simulates how domestic and local forces, leads to LUCC in peri-urban areas.	(Xie et al., 2005)
	ALUAM-AB	It simulates LUCC triggered by market and policy changes, considering farmers' preferences.	(Huber et al., 2012)

Conclusion Chapter 2

Geographic modelling, complexity and land use chapter was envisaged to provide an outline of both historical and current state of LUCC models. We introduced the bridge between classical geographical models and new modelling processes. The complexity of scientific research in the spatial and temporal dimensions are integrated to better understand human interactions.

A comprehensive discussion of the most common LUCC models was presented, and some statistical methods to measure models' accuracy were also identified. In this chapter, we illustrated the relevance of LUCC models, and how they should be applied and interpreted wisely so that modellers and decision-makers can take the best of what they can offer. In the next chapter, we will introduce to the topic of how LUCC modelling can be applied to land-use planning.

Chapter 3 - Land Use Planning and LUCC modelling

Introduction Chapter 3

Guaranteed food security and environmental preservation are required while encouraging economic growth are vital for society. Find a balance between these two perspectives is one of the biggest challenges faced by land-use planners and society. Land use planning controls where and how human impacts can be reduced at the local, regional and global level. It is addressed to regulate greenhouse emissions and to preserve flora and fauna biodiversity. Land-use planning must also identify better practices to protect soil, to promote landscapes restoration, to support environmental management, and to promote well-being.

In this chapter, we presented some policies and methods of land use planning, applied at European, national, regional, and local level.

1. Land use planning, agriculture and periurban areas

Land-use planning is an instrument to support better planning practices (UN, 1993). It aims to identify alternatives for land use and adopt the best land-use options, to allocate land uses to meet the environmental, social and economic needs of people while preserving future resources (Adams et al., 2016). It incorporates social and economic trends as well as physical and geographical elements. Land use planning is a public policy that describes and regulates the use of land to support local development goals. It creates legal and administrative instruments that support the plan, in which is defined the allocation, zoning, and the density of construction on the land. Land use planning comprises the anticipation of the necessity for change as well as responses to it, addressing strategies for territorial elements such as transportation, commercial, industrial, residential, economic growth, mitigating and adapting to climate change, as well as protecting people from natural disasters. These strategies must be addressed taking into account three main principles, efficiency, equity, and sustainability: (i) efficient by corresponding different land uses with the areas that will produce the highest profits at the smallest cost; (ii) equity by safeguarding some requisites such as food security, employment, as well as income security of people; and (iii) sustainability by recognising the current needs, while preserving resources for future generations (Healey, 1986; Lestrelin et al., 2011; Morgado, 2012; Selman, 1988).

The best principles for land use planning are those that both decision-makers and stakeholders can debate identifying the highest consensus about the goals of a specific territory, as well as those that incorporate the larger development vision (larger scale) for the locality (local scale). At a larger scale, land use planning, in many cases, establish the priorities balancing the competing demands for land in sectors such as the economy, tourism, housing and public amenities, road network, industries, as well as wildlife preservation. At the local scale, land use planning should be addressed to capture local stakeholders' knowledge, and contributions, and the actions taken locally (Kurz and Baudains, 2010; Milder, 2007).

1.1 European Union

Economic and social development determines undesirable effects on the environment. In Europe, to promote the spatial sustainability European Union (EU) created some policies to be applied in the EU territory. In 1999, the EU Council of Ministers established European Spatial Development Plan (ESDP). This plan aims to create general and common visions to develop national policies on spatial planning, while the diversity of national policies must be preserved. The intention to create the ESDP was to avoid disparities in European Union spatial planning, in order to achieve a more balanced between spatial planning and sustainable development; to create cooperation between urban and rural areas; to promote the polycentrism; to create economic and social cohesion; to preserve natural and cultural heritage; as well as to promote equal access to infrastructures and knowledge (Faludi, 2000; Shaw and Sykes, 2003).

EU has a great diversity of agricultural landscapes. Over time, biophysical conditions and farm management had a critical role in shaping landscapes. EU has recognized the importance to preserve agricultural landscapes, to promote agricultural competitiveness, internationalization, social inclusion, employment, sustainability, and the efficient use of resources (EC, 2012) by creating over time interlinked policy instruments such as the Convention on Biological Density in 1992; the Pan-European Biological and Landscape Diversity Strategy in 1995; as well as the European Landscape Convention in 2000. However, CAP and more recently the Rural development 2014-2020 (or 'the second pillar' of the CAP), they were instruments that have affected Europe's landscape changes, as well as helped to create measures to preserve and valorise rural landscapes resources. These instruments have been promoted by supporting local farmers (e.g., set-aside) (Berger et al., 2006); by encouraging rural development priorities to implement agricultural innovation in food chain, and climate-resilient economies (OECD, 2016); by developing local markets, to create short supply chains, jobs, new markets (based on local products); as well as by creating connections between consumers and producers (EC, 2011).

The effects of these EU policies in the supporting given to technological development have demonstrated that the "green revolution" has produced a deeply changed in a traditional rural landscape. These policies have also contributed, in some cases, to negatives effects on the environment such as the intensification (e.g., cause irreversible damage in soil quality), as well as the abandonment of less productive areas. However, as positive effects, these policies have brought positive demographic, social and economic impacts (Patel, 2013; Pingali, 2012).

1.2 Portugal

Over the last few decades, Portugal have registered significant increases in urban growth, particularly in medium and small urban areas, as a result of economic growth, purchasing power, improvements on road networks and transport infrastructure, as well as the development of public facilities (Abrantes, 2007; Marques da Costa, 2001). Portugal is a unitary state in which the Portuguese Constitution defines different jurisdictions and financial autonomies, and territorial entities:

i) national administration - includes the government (it sets the political orientations) and its departments (e.g., Directorate-General for Territorial Development (DGT), Commission for Regional Coordination and Development (CCDR), Directorate-General of Health (DGS), Institute for Nature Conservation and Forestry (ICNF), and The Portuguese Environment Agency (APA));
ii) regional governments of Madeira and Azores. They are run freely by elected councils and executive, with their regulatory decisions (spatial structuring and economic development) but are required to a legality control (national administration), in which their financial resources come largely from national administration; and
iii) local administration, in which integrates municipalities and municipal assemblies.

Portugal has different planning hierarchy levels and practices. They are established in the Portugal planning system by the Portuguese Framework Law for the Policy on Territorial Management and Urbanism - law LBGPPSOTU n. º 31/2014 of 30 May and NRJIGT n. º 80/2015 of 14 May, in which establishes the political-territorial development. This document specifies the spatial planning hierarchical framework from the national to the local level. The Portuguese spatial planning instruments and policies include four different types:

i) strategic. To define the territorial organization. It includes three programs: a) The National Program for the Territorial Management Policy (PNPOT), establish the conceptual framework for planning policy and the country's development model; b) The Regional Development Program (PROT), which defines the regional development model and includes recommendations at regional level (e.g., Regional Plan of Spatial Planning of Lisbon Metropolitan Area (PROTAML), Norte (PROT-Norte), Centro (PROTCENTRO), Alentejo (PROTALI), Algarve (PROT Algarve), Açores (PROTA), and Intermunicipal Programs);

ii) instruments of territorial planning. It includes the following laws in force: a) Municipal Master Plan (PDM), which regulates urban development, land use classifications, and land-use constraints; b) Urbanization Plan (PU) defines the urbanisation strategies, c) Detailed Plan (PP) that regulates the areas for construction; and d) the Inter-municipal spatial plan (PIOT) (however, this plan is not effectively applied);

iii) sectoral policy instruments. It outlines sectoral economic and social policies. Sectoral Plans (PS) include the Natura 2000 (it protects rare natural habitats), National Water Plan, National Forest Plan, and National Road Plan; and

iv) special plans (PEOT). These plans define the land classification that protects national parks, artificial lakes, and coastal areas (e.g., Protected Area Management Plans - POAP, Water Supply Management Plans - POAAP, and Coastal Areas Management Plans - POOC).

These spatial planning instruments and policies described above have different scales of implementation. They are described in Table 3.1.

Table 3.1 – Territorial management instruments.

Scale	Territorial instruments	Scope
National	**PNPOT**	Strategic
	PS	Sectorial
	PEOT	Specific scope
Regional	**PROT**	Strategic
Local	**PIOT**	Strategic
	PDM, PU, PP	Regulatory

In addition to the mention spatial planning instruments and policies, there are legal frameworks (included in the legislative system) which have the goal to protect the environmental systems such as the National Agricultural Reserve (RAN) and National Ecological Reserve (REN).

RAN was created in 1982 to identify, to regulate and to protect the best agricultural soils (soils of high suitability for agriculture), and to prevent the built-up areas occupation. REN was established in 1983 to identify and controls biophysical structures and elements with high ecological value and sensitivity (e.g., maximum infiltration soils, hilly slopes, river basin head, floodable areas, beaches and dunes). REN was considered a pioneering legal framework in environmental protection. Both RAN and REN are implemented at municipal land use plan. REN delimitation is mandatory and does not allow urban construction.

1.3 Agricultural land use planning in peri-urban areas: from European to local policies

Farming in peri-urban areas is imperative to supply people needs for healthy and local food. New emerging consumption pattern in the EU, the increasing pressure on existing resources (e.g., urban development), or climate change is putting societies facing some challenges. Peri-urban agriculture has a central role in the direction to a sustainable model, that needs to have as a primary goal the maximisation of agricultural production and the minimisation of environmental impacts.

Particularly in the European Union, policies are being implemented to promote short food-supply and to endorse more competitiveness for agricultural land in these areas. They have also been created to support sustainable management actions in agricultural areas, to reduce land degradation, to preserve food security, and to endorse a multifunctional and high-quality agriculture. Europe's CAP is an important instrument that defines rules and regulations for farming. The introduction of CAP in 1990, have forced the restructuring of agricultural land to be more competitive for global markets (Pinto-Correia and Vos, 2004). The central restructuring was based on high-production areas to better manage them with machines. In 2013, a reform of CAP was introduced, defining new rules and regulations for the period 2014-2020. This reform included opportunities for farming in peri-urban regions, with better support for local food, and short supply chains.

Another policy, that was created at the European Union level, was the European Agricultural Fund for Rural Development (EAFRD) in which the main purpose was to develop connections between rural and urban areas. In the same decade (in 2004), the European Economic and Social Committee (EESC) created the initiative ‘Opinion on Agriculture in Peri-urban Areas’, in which identified measures to support conservation, planning and management of peri-urban areas with agricultural activity. One of the suggestions was to implement a European Observatory to create sustainable management and development plans based on the promotion of food quality and in new activities in peri-urban areas related to leisure, environmental education, and ecotourism. This observatory aided to increase consciousness of agriculture’s role in the relationship between cities and countryside.

In 2010, the European Union launched the initiative Europe 2020, a ten-year strategy that aimed to create sustainable agriculture with inclusive growth, by promoting employment, climate change mitigation, biodiversity preservation, and cultural heritage valorisation.

Other initiatives have been created to promote farming in peri-urban regions. In the 2000s was created a European network called PURPLE that aimed to endorse European policies and regulation for peri-urban areas, establishing good practices among European Union, and to guarantee the food production close to large populations.

All of these mentioned initiatives have increased awareness about the challenges that farming is facing in peri-urban regions in Europe. However, more should be done especially the need to integrate all these initiatives in all European Union policy areas. In the peri-urban regions as a dynamic and changing area (Lambin et al., 2003), decision-makers have the challenge to create on-going planning instruments to follow the rapid changes that are verified. They are responsible for addressing land-use strategies (Bryant et al., 2010; Fazal et al., 2015; Gutzler et al., 2015; Sakieh et al., 2015; Valbuena et al., 2010b), in which incorporate multiple environmental, demographic and socioeconomic indicators is needed.

In Europe, some policies have been successfully implemented in the protection of agricultural land, such as the SCOT (Schéma de Cohérence Territoriale) in France. SCOT is a master plan framing zoning that aims to preserve farming in peri-urban areas for curtailing urban sprawl, in which comprise prospective and monitoring analysis to support territorial diagnostics. This plan has been effective in decreasing farmland conversion (Desjardins and Leroux, 2007).

In Portugal, agricultural preservation has been recognised as a strategic priority in spatial planning, where land protection policies have been created to control land conversion from productive agricultural land to other land uses. Its preservation has been received special attention in some previously mentioned spatial planning instruments and policies and legal frameworks (e.g., PNPOT, PROT, PDM, and RAN). Some of these measures have been related to increasing soil productivity, to safeguarding the quality of the landscape, to guarantee water sustainability, to improve agricultural competitiveness, as well as to encourage more sustainable agriculture. However, agricultural land remains being converted (Abrantes, 2007), despite the existence of these policies. There has been a dissonance between what these plans contemplate, and what happens in land transformation. They have had difficulty in recognising the importance of agriculture in the strategic planning and its influence on the life of urban areas, especially in peri-urban areas where land conversion occurs faster. It is needed to rethink this time lag and reconsidering about how to create measures to speed up the decision-making processes because usually, they do not respond immediately (or effectively) to social and economic transformations. A change from top-down administrative ‘government’ is needed in the sense of being more inclusive, adaptive and at multilevel decision-making. This perception is critical for the sustainable management of social-ecological systems.

2. Methods to integrate stakeholders’ participation in land use analysis and planning

The engagement of stakeholders in land use planning is critical to capture their knowledge and to identify their visions and concerns. In Portugal, some scientific projects have addressed these issues such as DAUME (Durabilité de l'agriculture (Peri) urbanisée en Méditerranée) and AgriMet-MOD. DAUME project aimed to evaluate governance forms of agriculture in peri-urban regions, whereas AgriMet-MOD aimed to create technical and political recommendations to integrate agriculture into the spatial planning system. An interest for closer cooperation between decision-makers and researchers have been increasing.

In our research analysis, we performed public participation with stakeholders, supported by spatial scenarios to identify alternative futures. Below, we will develop these two main topics: public participation and spatial scenarios for alternative futures.

2.1 Public participation

To fill the gap between stakeholders' visions and decision-makers, participatory methods to connect both sides have been growing. One of the first works concerning participatory actions was written by Sherry Arnstei in the 1960s entitled "*A Ladder of Citizen Participation*" (1969) to promote public participation. In 1971 U.S. Department of Transportation created some premises where decision-makers and stakeholders firstly discussed the concepts of participatory planning. In the 1990s, in France, Michael Godet (2008) established the concept of geoprospective that aimed to forecast the future of spaces and to estimate the influence of spatial dimension (Abrantes et al., 2016). One decade later, in 2001 Fred Fisher wrote one of the most critical documents recognising the participatory planning as part of the planning process, the *Building Bridges through Participatory Planning* (Fisher, 2001).

Public participatory focused on the systematic evaluation of land use alternatives (Chen et al., 2003) intend to support decision-makers in the promotion of land-use sustainability and the needs of the local population (Bartke and Schwarze, 2015; Houet et al., 2017). It can reduce problem complexity, identifying uncertainties and sharing knowledge between stakeholders, and mitigate goals divergences (Gwaleba and Masum, 2018; Labiosa et al., 2013), as well as to create relevant information-gap tasks, and to encourage active discussion. Public participation was developed based on the principle to create impartial judgements (Nyumba et al., 2018) and to promote an inclusive process to address demographic, social, economic, political and environmental issues. It can be conceptualized for design (i.e. communication), analysis (i.e. spatial evaluation), and negotiation (i.e. interactive decision support) (Carton and Thissen, 2009), in which should be incorporated a) study purpose; b) available data; c) methods, tools, and data structure used to achieve the objectives of the study; d) outcomes; and e) discussion and validation. Public participation has been an ongoing topic in municipal planning policies (Bonsu et al., 2017). At the local level, participation is related to the inclusion of a wide range of stakeholder's visions at different stages of the decision-making planning process (Cascetta and Pagliara, 2013). The main contribution of participation are related to promoting the legitimacy of decisions, to reduce conflicts, to include local knowledge, to validate outcomes, and to produce a shared understanding of land use strategies (Brown et al., 2018; Llambí et al., 2005; McCall, 2003). Finding better ways of gathering data and designing better tools for getting input into the decision-making process can play an essential role in public participation (Al-Kodmany, 2001). In land use analysis spatial scenarios are one of these forms (Pettit, 2005) to help decision-makers to evaluate LUCC impacts (Francis and Hamm, 2011; Jantz et al., 2010), as well as to make better decisions (Brits et al., 2014; Goldstein et al., 2012). Land-use planning supported by different stakeholders has been demonstrated be quite efficient, helpful, able to support spatial planning and to answer any questions about land conversion and location (Ghavami et al., 2017). They also can provide a helpful baseline, and valued information about future demands to support strategic policies.

At the beginning of public participation to identify the best land use alternatives, large copies of maps were used to discuss proposed plans (Burrough and McDonnell, 1998). However, in the most recent years, this process has been accomplished by GIS technologies (Longley et al., 1999), as a support instrument that focuses on visualisation, organising and assessing spatial data. In this way different approaches have been applied using GIS technologies in order to be more integrative for stakeholders participation, such as the concepts of Participatory GIS (McCall, 2003) focused on Public Participation (PPGIS), e.g., Wolf et al. (2015), and Group Spatial Decision Support Systems (GSDSS) e.g., MacEachren (2000). PPGIS enable to assess the geospatial data providing simultaneously participatory knowledge (Brown et al., 2018), while, GSDSS fills the gap of PPGIS in supporting the identification of potential conflicts and negotiation among stakeholders (Di Zio et al., 2017).

Also, another participatory GIS technique is Spatial Decision Support Systems (SDSS) (Malczewski, 2006). SDSS is one of the widely used computer-aided planning systems (Geertman, 2002). It comprises managing, testing, building and visualising different scenarios, planning, monitoring and evaluating methods. To develop SDSS different steps need to be performed such as the identification of the problem, data collections, statistical analysis, scenario building, assessment of strategy, and participation and collaborative decision-making. SDSS has three main principles: (i) integration of GIS technology; (ii) use of different data types, model algorithms and interactive communication between the user and the system; and (iii) a tool for decision-makers. Previous studies have discussed the effectiveness of collaborative SDSS, e.g., Chakhar et al. (2008) and Crossland et al. (1995). Its efficacy may contain usefulness (to support a specific goal), and clarity (the capability to recognise the data provided). Several well-known SDSS have been applied in the last years. Among such existing SDSS is What-if? (Klosterman, 1999), RAMCO (Uljee et al., 1999), UrbanSim (Waddell, 2002), CUF (Landis, 1994), INDEX (Condon et al., 2009), CommunityViz (Walker and Daniels, 2011), CITYgreen (Jantz and Manuel, 2013), SLEUTH (Chaudhuri and Clarke, 2013), and KLUM (Ronneberger, 2005) frameworks (Table 3.2).

Table 3.2 – SDSS framework.

SDSS Framework	Description	Source
What-if?	Collaborative GIS-based planning support system. "What-if" projects land use, population and employment.	(Klosterman, 1999)
RAMCO	Decision support environment for the management of coastal zones through the rapid assessment of problems.	(Uljee et al., 1999)
UrbanSim	Supports metropolitan land use, transportation, and environmental planning.	(Waddell, 2002)
CUF	Integrates population prediction and spatial allocation.	(Landis, 1994)
INDEX	Evaluate the advantages and disadvantages of planning scenarios.	(Condon et al., 2009)
CommunityViz	It supports city planning, land use planning, resources, environmental protection, and transportation planning.	(Walker and Daniels, 2011)
CITYgreen	Analyse climate, air quality, water regulation, water purification, water treatment, and extreme events.	(Jantz and Manuel, 2013)
SLEUTH	Predict urban growth.	(Chaudhuri and Clarke, 2013)
KLUM	Assess future agriculture land changes on a global scale.	(Ronneberger, 2005)

These frameworks have in common the knowledge sharing between stakeholders, experts, decision-makers and end-users, being a critical step to endorse conflict-solving and to reach consensus (Doi and Kii, 2012). They offer an easy-to-understanding interface to aid planners to analyse spatial data and to support planning decisions on long-term policy assessment by creating land-use strategies. They aim to promote efficient use of land to identify optimal land use allocation; and to recognise how better land use can be managed by evaluating impacts of alternative land use.

Although the advantages mentioned above, public participation to analyse and validate future alternatives for land use is yet seen as complex (Asgesen and Dragicevic, 2014), and difficult to apply to planning policies. In Portugal, these approaches at the municipal level are still scarce.

2.2 Spatial scenarios for alternative futures

Scenarios as a method to support public participation have been used to identify future uncertainties in endogenous and exogenous developments (Rounsevell et al., 2006) and to provide strategic support for decision-makers and researchers to evaluate potential future alternatives (Porter, 1985) with relevant implications for land management (Bonsu et al., 2017; Kröger and Schäfer, 2016; Pocewicz et al., 2008). Spatial scenarios help to build multiple futures focused on competing for development (Xiang and Clarke, 2003) and to create and understand various planning strategies.

Researchers have been developing scenarios since the 1990s. Scenarios indicate perceptions about alternative futures, and hypotheses that can be tested (Schwartz, 1996). Scenarios are seen as a method to obtain future images (Schoemaker, 1995) and to manage future uncertainties (Godet, 2000; Ringland, 1998). The European Environment Agency (EEA) (EEA, 2011) defines a scenario as a tool that represents complex targeted information to policy-makers and the public. Scenarios are narratives that connect current and historical events with hypothetical events that may take place in the future. Scenarios must be reliable, based on good arguments, identify any potential problem, identify alternatives, and project future images. Scenarios, as part of planning policies, can play an important role in territorial management instruments by integrating qualitative and narrative descriptions that should explain quantitative scenario descriptions. Scenarios are not predictions but ask questions, such as ‘what can happen?’, ‘what happens if?’. They should identify the stakeholders, the object, and the time-period (Scearce et al. 2004). The scenario must answer: where? why? and when? (Lambin, 1994). Borjeson (2006) identified three scenarios categories: predictive, explorative and normative. Each one is subdivided into two types (Fig. 3.1).

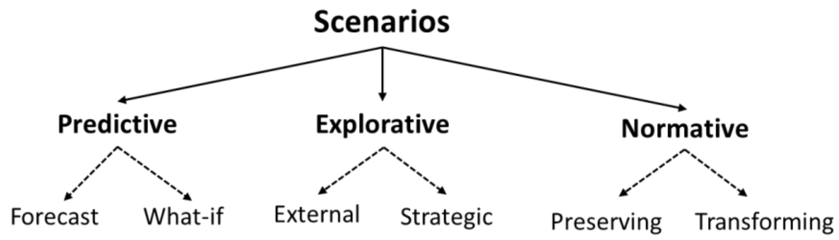

Figure 3.1 – Scenarios categories and types (adapted from Borjeson et al. 2006)**.**

Predictive scenarios can be divided into forecasts and what-if. According to Borjeson (2006), projections scenarios answer the question *"what will happen to the most likely development unfolds"?* And in a what-if type scenario, answers to the question "*what will happen, on the condition of some specific events"?* The term what if is presented when there are probably effects at different visions (Scearce, 2004).

Explorative scenarios are also divided into two types: external and strategic. External scenarios have external dynamics, beyond the control of the relevant actors. On the other hand, strategic scenarios integrate internal factors, which define a collection of probable consequences for strategic decisions. These scenarios answer the following question: *"what can happen if we act in a certain way"?* (Höjer et al., 2008).

Finally, normative scenarios are divided into preserving and transforming. Preserving scenarios are established, to find how a target can be reached, within a predominant structure; and, transforming scenarios are used when a trend break is required to achieve a goal.

Scenarios are presented as qualitative and quantitative. In a qualitative way, scenarios are presented descriptively or/and by visual symbols (diagrams). The major disadvantage of qualitative scenarios is related to the absence of numerical information (Alcamo, 2001; Varho and Tapio, 2013). Borjeson et al. (2006) presented the main characteristics of each category summarily, and the type of scenario (Table 3.3).

Table 3.3 – Scenario types (adapted from Borjeson et al. 2006).

Scenario (type)	Quantitative/ Qualitative	Time-frame
	Predictive – what will happen?	
Forecasts	more quantitative; less qualitative	usually short
What-if	more quantitative; less qualitative	usually short
	Explorative – what can happen?	
External	more qualitative; less quantitative	usually long
Strategic	quantitative and qualitative	usually long
	Normative – how can a certain target be reached?	
Preserving	more quantitative	usually long
Transforming	more qualitative; some quantitative	long

One of the most well-known future scenarios as support for policymakers was developed by the Intergovernmental Panel on Climate Change (IPCC) in Special Report on Energy Scenarios (SRES) in 2000 (Nakicenovic and Swart, 2000). This report defines possible future climate change with four narrative storylines (A1, A2, B1, and B2), setting global scenarios for the 21st century (Table 3.4). These scenarios aimed to mitigate issues such as human intervention to reduce the sources of greenhouse gases, and to better plan human settlements, and infrastructures.

Table 3.4– SRES (adapted from Nakicenovic and Swart, 2000)**.**

Scenario	Description
A1	- Rapid economic growth. - A global population reaches 9 billion in 2050. - Extensive social and cultural interactions worldwide
A2	- Self-reliant nations. - Increasing population. - Regionally oriented economic development.
B1	- Rapid economic and population growth. - Clean and resource-efficient technologies. - Global solutions to economic, social and environmental stability.
B2	- Continuously increasing the population. - Emphasis on local rather than global solutions. - Intermediate levels of economic development.

In the last years, other global models have been developed by OECD Environmental Outlook 2050 (creating bridges between science and policy realms) (OECD, 2012), World Bank (2010), The European Environment State and Outlook 2015 (makes a reflection on European environment) (EEA, 2015), Models IMAGE (Integrated Model to Assess the Global Environment - simulates the environmental consequences of human activities) (The Government Office for Science, 2011), GLOBIOM (to assess competition for land use between agriculture, bioenergy, and forestry – global scale) (IIASA, 2014), and FAO (2013) (aims to create a Climate-Smart Agriculture at regional and local scale). These models have in common the integration of planning measures.

Scenarios have been used in land use science since the 1960s. The first works were a study regarding urban growth in the Detroit area (Doxiadis, 1966), and a study concerning regional land-use planning (METLAND) (Fabos et al., 1978). Land-use scenarios have as the main goal to recognise the uncertainties to better prepare the future (Cork et al., 2000), and to promote desirable land uses (Leão et al., 2004a). Scenarios have been increasingly used as decision support tools to provide strategic urban planning (Hill and Lindner, 2010; Houet et al., 2016) and to identify spatial planning actors intentions (Ligtenberg et al., 2001). They help decision-makers to anticipate potential futures (Aalders, 2008; Fonderflick et al., 2010), to assess extreme alternative prospects, and to create planning strategies.

Integrating spatial scenarios into adaptive planning incorporates different steps. This process can answer to different hypotheses (Rauws and De Roo, 2016), such as to identify the problem (in collaboration with stakeholders), to select driving forces, and to define a time scale. Cork et al. (2000) identified the following characteristics which scenarios should have: (1) driving forces that had the most relevance in the past; (2) driving forces that will have a great importance for changes in the future; (3) explore the uncertainties; and (4) identify the needs to be addressed in the present to prepare the future. The last steps to prepare a scenario planning consists of returning to the original question, and answer with different scenarios (Wulf et al., 2010).

Conclusion Chapter 3

Land-use planning strategies are focused on opportunities, organisational strengths and framing processes. It is defined as support for decision-makers to develop skills and to lead to better decisions about future land use actions. Spatial scenarios can anticipate and understand human’s behaviours, and they can improve the communication between stakeholders, identification of potential conflicts, and create strategies to apply in the land use planning context.

While new planning standards such as compact urban development and polycentric development have been encouraged, urban sprawl and the loss of agricultural land remains as one of the significant challenges in Europe and in Portugal. It was found that the lack of effective spatial planning has resulted in uncoordinated urban outgrowth.

This chapter described the land use planning in Europe and in Portugal, recognizing how different stakeholders can be mobilized to participate in the decision-making process, and how land-use planning can play a key role in guiding agricultural preservation, to contribute for better decisions, and to promote land-use sustainability in the context of peri-urban areas.

Conclusion PART ONE

Preserve agricultural land is a critical issue for generating food security and preserve biodiversity to support our livelihood. Since it is not possible to avoid land artificialization, it is important to continue developing methods to improve our understanding of land use management. Complexity science can provide an epistemological approach to better recognise the evolution and prediction of land-use dynamics. It can help planners in the decision-making process clarifying unpredictable conditions, identifying, in time and space, plausible future images, and ensuring a better quality of the living environment.

The development of LUCC models can become an essential tool for spatial planning (Herold et al., 2005). A better LUCC analysis can support better-planning practices (de Kok et al. 2001; FAO 1993; Yirsaw et al. 2017) and identify the valuation of different land use options and socioeconomic settings to identify desirable land uses (FAO 1993). Land use planning provides policies to promote regulatory land-use implemented by decision-makers. These plans intend to control land use activities in the future, to preserve open landscapes for agriculture and nature, and to encourage sustainable development. However, these plans are too rigid especially when applied to peri-urban areas where land conversion occurs very fast. Thus, land use planning and decision-making processes applied to peri-urban areas are one of the significant policy challenges at the moment, and more studies are needed (Abrantes et al., 2016a).

The greater proximity to urban development has been increasing farmland prices (Guiling et al., 2009). The proximity to urban settlements and the urban pressure felt in these places' present farmers with new challenges for the future. The literature focuses on three main challenges: maintaining their farmland (Malan, 2015); expanding their farmland (Deininger and Byerlee, 2011); and selling their farmland for urban development (Curran-Cournane et al., 2016; Satterthwaite et al., 2010). Analyse and understand how farmers would change the territory are of great importance to anticipate the uncertainties of the future.

Although complexity science has been applied by some researchers in simulating LUCC (Fu et al., 2018; Sang et al., 2011), few studies have combined participatory planning from the LUCC perspective.

In the next Part, we will introduce the data and methods used in our case study and the results achieved to identify the LUCC transformations.

Part Two: Measurement of LUCC in Torres Vedras (Portugal)

Introduction PART TWO

Part Two Measurement of LUCC in Torres Vedras (Portugal) is divided into two chapters. Firstly, in chapter 4, the GIS data (acquisition, management, storage, and normalization), and the case study were presented. Secondly, in chapter 5, a detailed description of the agricultural land use dynamics in Torres Vedras municipality over time, using different techniques were shown.

We focused our analysis on measuring the influence of urban growth, and its impacts on agricultural land-use change and fragmentation.

Chapter 4 – Study area, GIS data acquisition and management

Introduction Chapter 4

In this chapter we presented the case study and the driving forces used. These data were supported by GIS technology, which allowed to organise, manage, monitor, display, analyse, and to provide a standardised and verified set of core data. The use of spatial data allowed to understand complex spatial analysis, to interpret, to visualise geographically referenced information, and to identify spatial relations, patterns, and trends.

1. Torres Vedras (Portugal): the case study

Torres Vedras Municipality (Portugal) is located roughly 50 km north of Lisbon - bathed by the Atlantic Ocean and is located on the western edge of the European continent. Torres Vedras covers an area of about 407 sq. Km, and is divided into 13 parishes (Fig. 4.1). The elevation ranges from the sea level to 395 m. The orographic effect and the Atlantic Ocean are a major control on temperature and precipitation, in which the average annual temperature is 15ºC, and the average annual rainfall is 682 mm. Torres Vedras is characterized by mild temperatures during the colder months, near absence of frost on the coastline, high air humidity throughout the year, and low thermal amplitudes (IPMA, 2019).

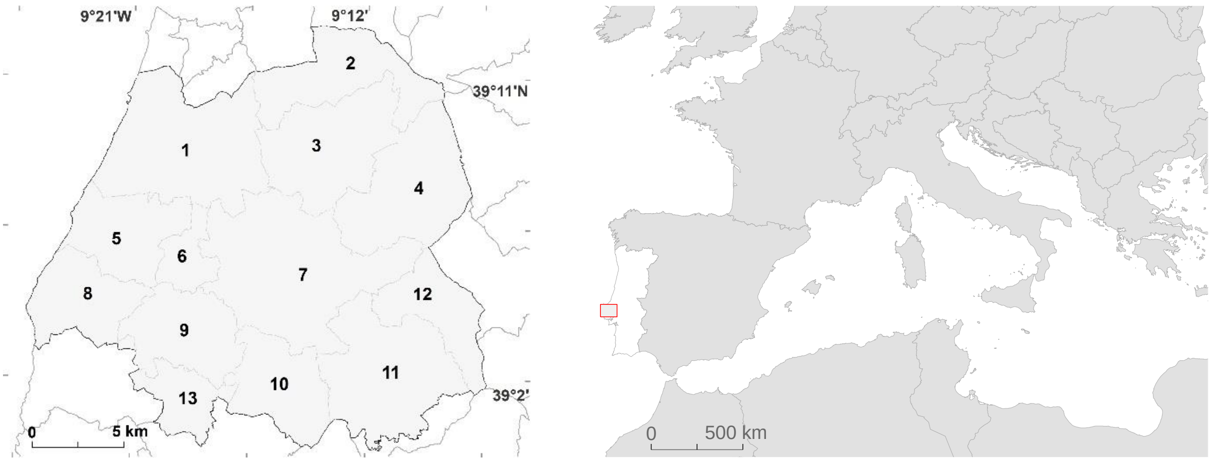

Figure 4.1 – Location of Torres Vedras Municipality (Portugal) in Europe. Parishes: 1 - União das freguesias de A dos Cunhados e Maceira; 2 - União das freguesias de Campelos e Outeiro da Cabeça; 3 - Ramalhal; 4 - União das freguesias de Maxial e Monte Redondo; 5 - Silveira; 6 - Ponte do Rol; 7 - União das freguesias de Torres Vedras (São Pedro, Santiago, Santa Maria do Castelo e São Miguel) e Matacães; 8 - São Pedro da Cadeira; 9 - Ventosa; 10 - Turcifal; 11 - União das freguesias de Dois Portos e Runa; 12 - Carvoeira e Carmões; 13 - Freiria (data source: (DGT, 2018)).

Over the past two decades, Torres Vedras has been dominated by a rapidly growing urban expansion, and its population has been increasing since the late 1980s (Statistics Portugal, 2011). In 2011, Torres Vedras Municipality (Portugal) had a population of 79,465 inhabitants, and a population density of 195 inhabitants per sq. Km (Fig. 4.2).

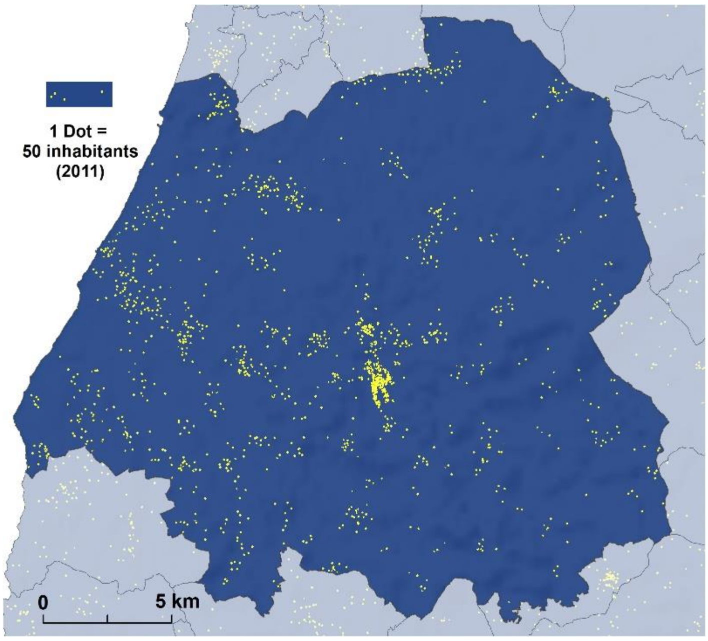

Figure 4.2 – Inhabitants in Torres Vedras (2011), by statistical sub-sections (data source: Statistics Portugal, 2011).

During 1991-2011 Torres Vedras registered a population growth of 18% (Table 4.1). However, this growth has not been the same throughout the municipality. During this period, Santa Maria do Castelo e São Miguel and, A dos Cunhados parishes had a population growth around 47%, and 37%, respectively. Nevertheless, some other parishes had a negative population growth, such as Outeiro da Cabeça (-15%), and Matacães (-16%).

Table 4.1 – Resident population and population density, in Torres Vedras (data source: Statistics Portugal, 1991, 2001, and 2011).

Year	Resident population	Population density
2011	79,465	165
2001	72,250	177
1991	67,185	195

The A8 motorway, connecting to Lisbon and opened in 1996, it was of great importance for the urban expansion in Torres Vedras. Between 1995 and 2010, an urban increase by 41% was registered (data source: DGT, 1995, 2010), accompanied by an economic and social improve, since the late 1990s.

New business models characterise Torres Vedras responding to the challenges the agricultural industry is facing in areas of high urban pressure. This area is marked by farmers, who are dedicated to maintaining their agricultural activity; diversified crops; small-sized farmlands; and adoption of new technologies for farming (Statistics Portugal, 2011). However, in 2009, 43% of the farming population of Torres Vedras was aged over 65, in which the farming population has been declining. In 1989, there were 7,185 farmers; and in the most recent census (2009), there were 2,201, which represent a decrease of 226% (Table 4.2). The same trend occurred both nationally (-96%) and regionally – Oeste Region (-186%) for the same period.

Table 4.2 – Farmers by age group, in Torres Vedras (data source: Statistics Portugal, 1989, 1999, and 2009)**.**

Year\Age group	Total	15-34	35-64	65+
2009	2,201	64	1,208	929
1999	3,995	196	2,512	1,287
1989	7,185	612	4,897	1,676

The agriculture sector has always been an essential sector in Torres Vedras (Statistics Portugal, 2011). However, in the past few years, agricultural land has been declining, which has been resulted in agricultural land fragmentation. It has been caused by many environmental, demographic and economic factors, such as a decrease in farmer population, a decrease of the used agricultural area, and an increasing demand for urban development. The agricultural land decreased has been also accompanied by a decrease in the number of farmlands. In 1989 was 7,245, and in 2009, 2,337, registering a decrease of 210% (Table 4.3).

Table 4.3 – Number of farmlands and UAA, in Torres Vedras (data source: Statistics Portugal, 1989, 1999, and 2009).

	2009	1999	1989
N. º of farmlands	2,337	4,111	7,245
UUA (ha)	29,064	33,524	42,761

Torres Vedras is one of the leading suppliers of agricultural goods in Portugal (e.g., fresh fruits, vegetables, and wine) (Statistics Portugal, 2011), in which is one of the most critical sectors of the local economy (Statistics Portugal, 2009). The gross added-value of agricultural enterprises in Torres Vedras has increased by 63% in the last few years (2009-2016), which compares with 45% in the whole Oeste Region, and 57% nationwide.

The average annual work (AAW) unit by 100 hectares of utilised agricultural areas has also been decreased. In 1989 was 42.7, in 1999 it was 32.9, and in 2009 it was 25. Torres Vedras is characterised by farming systems heterogeneity, playing an essential role at both local and regional scale. In the last years, Torres Vedras has been losing a considerable part of their agricultural land to urban land in the face of rapid urbanisation. The increased land competition and the demand for land have led to the parcels' fragmentation. Productive agricultural land and natural protected areas have been decreased and subdivided into small parcels. Urban development has contributed to the decreasing of farmland, increasing the speculative urban pressure on the land market (Gomes et al., 2019a, 2019b).

Regarding the land use composition, Torres Vedras is mainly covered (in 2010) by forest and semi-natural areas (about 40% of the total area), permanent crops and heterogeneous agricultural land (25.94%), artificial surfaces (11.54%), permanently irrigated land (11%), non-irrigated arable land (9.09%), pastures (2.17%), and water bodies and wetlands (0.15%) (DGT, 1995, 2010). Table 4.4 provides a detailed description of the subclasses included in each land-use class (in %).

Table 4.4 – Land use classes and subclasses (data source: DGT, 2010).

Land Use Class	Land use subclasses	2010 (%) - subclasses	2010 (%) - classes
1 - Artificial surfaces	Urban fabric	7.09	11.40
	Industrial, commercial and transport units	2.45	
	Mines, dumps and construction sites	1.46	
	Artificial, non-agricultural vegetated areas	0.40	
2 - Non-irrigated arable land	With and without dispersed vegetation	9.09	9.09
3 - Permanently irrigated land	Permanently irrigated land	11.00	11.00
4 - Permanent crops, and heterogeneous agricultural land	Vineyards	13.68	25.94
	Orchards	3.51	
	Olive groves	0.04	
	Complex cultivation patterns	7.18	
	Annual crops associated with permanent crops	0.95	
	Land principally occupied by agriculture	0.56	
	Agroforestry areas	0.02	
5 - Pastures	Grassland (pastures and meadows)	2.17	2.17
6 - Forest and semi-natural areas	Broad-leaved forests	16.16	39.94
	Coniferous forest	0.86	
	Mixed forests	2.44	
	Scrub and herbaceous vegetation associations	19.89	
	Open spaces with little or no vegetation	0.60	
7 - Water bodies and wetlands	Water bodies	0.15	0.46
	Wetlands	0.31	

Evolution: 1995-2007-2010

Torres Vedras, as well as other rural-urban transitional areas, is characterised by a highly dynamic LUCC. Actual land use data from 1995 to 2010 were compared. Artificial surfaces increased by 41.5%, and non-irrigated land increased by 3% from 1995 to 2010. Meanwhile, non-irrigated arable land, permanently irrigated land, permanent crops, and heterogeneous agricultural land decreased overall to 41% (pastures decreased -73.8%, followed by the permanent crops and heterogeneous agricultural land at -22.3%, and by the permanently irrigated land at -10%). Also, according to the land-use transition matrix, we observed that 11% of forest and semi-natural areas, and 10% of permanent crops, and heterogeneous agricultural land were transformed into artificial surfaces. Moreover, 37% of permanent crops and heterogeneous agricultural land were converted into non-irrigated arable land (Figure 4.3).

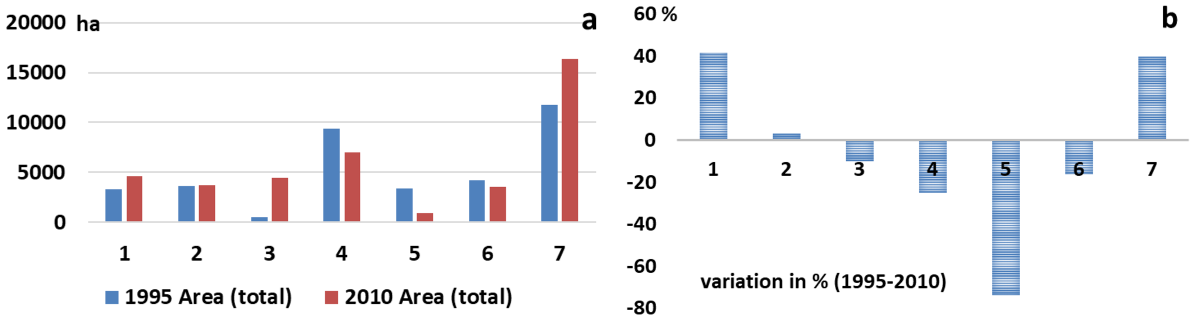

Figure 4.3 – (a) Total area (in hectares) by land-use class in 1995 and 2010; (b) variation (in %) by land-use class between 1995 and 2010. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops; 5 - pastures; 6 - heterogeneous agricultural land; and 7 - forest and semi-natural areas (data source: DGT, 1995, 2010).

The transition analysis between 1995 and 2010 demonstrates that LUCC were significantly higher in some land-use classes. 52.5 ha of forest and semi-natural areas in 1995 had been converted into artificial surfaces by 2010. During the same period, 214.9 ha of pastures had been converted into the forest and semi-natural areas. Moreover, between 1995 and 2010, 92 ha that had been permanent crops in 1995 had been converted into non-irrigated arable land in that period (Fig. 4.4).

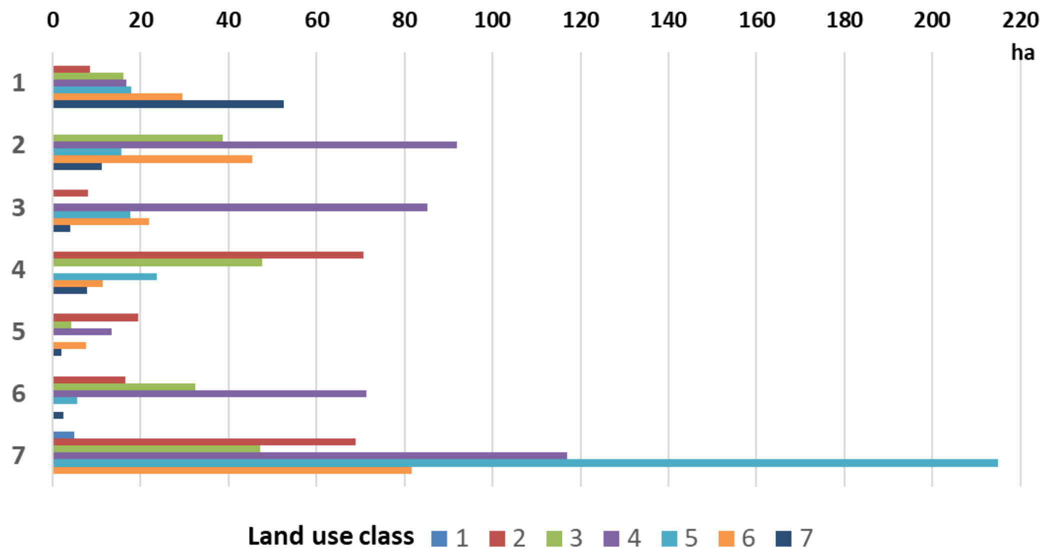

Figure 4.4 – (a) Total area (in hectares) by land-use class in 1995 and 2010; (b) variation (in %) by land-use class between 1995 and 2010. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops; 5 - pastures; 6 - heterogeneous agricultural land; and 7 - forest and semi-natural areas (data source: DGT, 1995, 2010).

2. GIS data acquisition and management

Data were stored and managed in a geodatabase. Some studies have been carried out concerning the usability of data at different spatial resolutions. Large spatial resolutions make difficult the identification of detailed information. However, small spatial resolutions have the advantage of accurate resolution data, facilitating the identification of land use relationships, which is relevant to suggest and implement local sustainable environmental policies (Pan et al., 2010; Stanilov and Batty, 2011). This is one of the most important procedures for planning and decision making (Antrop, 2004; Antrop and Van Eetvelde, 2000; Meeus and Gulinck, 2008; White and Engelen, 2000).

In our research, our data is in the ETRS89/PT–TM06 projection system, and it was converted into raster format with a 1 ha resolution. The choice of the spatial resolution resulted from a trade-off between data costs, computer processing time, reliability, feasibility, and the ecological fallacy. A small spatial resolution has the advantage of providing detailed land-use data and facilitates the identification of land use relationships (Pan et al., 2010; Stanilov and Batty, 2011).

2.1 Land use/cover

Land cover maps for 1995, 2007, and 2010 at the 1:25,000 scale (the most updated and detailed data for the study area) were selected for this research. Original data is organised into 193 different land use/cover classes. The land cover was regrouped into 7 classes: 1 – artificial surfaces; 2 – non-irrigated arable land, 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas; and 7 – water bodies and wetlands (data source: DGT, 1995, 2010) (Fig. 4.5).

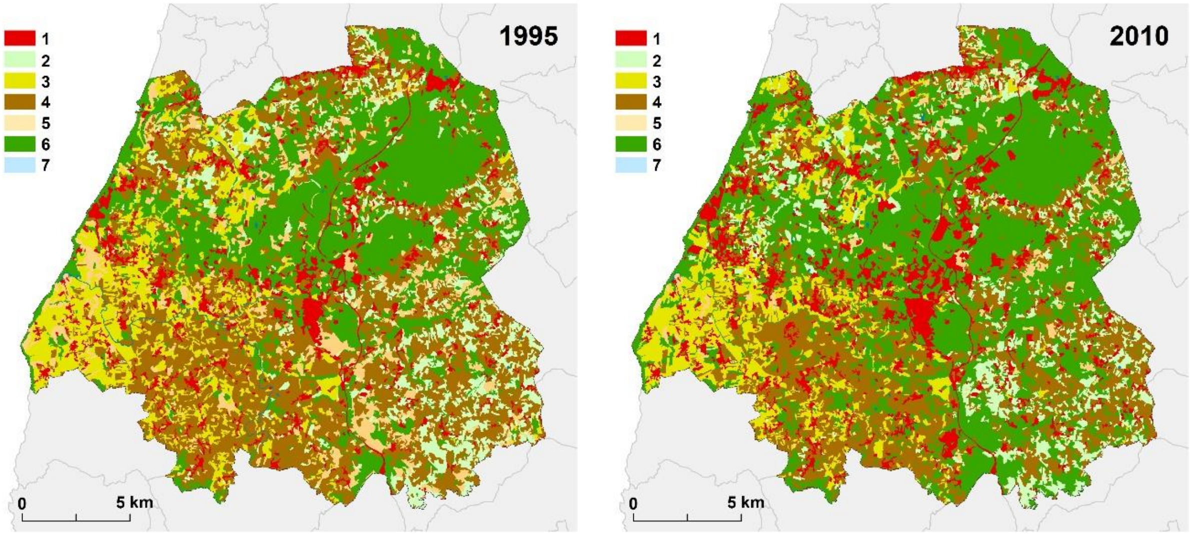

Figure 4.5 – Land use cover 1995 and 2010 (Torres Vedras, Portugal) (data source: DGT, 1995, 2010).

Artificial surfaces were grouped in the same land-use class due to the urban fabric and service growth, usually accompanied by population growth (Duranton and Puga, 2014; Satterthwaite et al., 2010). However, we divided agricultural land into four land use classes because the focus of this study was to provide an in-depth analysis of agricultural land use dynamics. Forest and semi-natural areas were grouped into one land-use class, as well as water bodies and wetlands. Following, we described in detail each of these seven land use classes:

- (1) artificial surfaces: The Organisation for Economic Co-operation and Development (OECD), Eurostat and Directorate General Regional Policy (DG REGIO) defined artificial surfaces as the functional urban areas according to population size, and land-use activities. It includes continuous and discontinuous urban areas, industrial, commercial and transport units, road and rail networks, dump sites and extraction sites, and green urban areas;
- (2) non-irrigated arable land includes cereals, legumes, fodder crops, root crops and fallow land, flowers and tree (nurseries cultivation and vegetables, whether open field or under plastic or glass (includes market gardening), aromatic, medicinal and culinary plants;
- (3) permanently irrigated land comprises crops irrigated permanently or periodically, using a permanent infrastructure (irrigation channels, drainage network);

- (4) permanent crops and heterogeneous agricultural land incorporate vineyards, fruit trees and berry plantations (parcels planted with fruit trees or shrubs) olive groves, annual crops, and complex cultivation patterns (the juxtaposition of small parcels of diverse annual crops);
- (5) pastures combine dense grass cover, of floral composition, dominated by Graminaceae, not under a rotation system;
- (6) forest and semi-natural areas include broad-leaved forest; coniferous forest; mixed forest; shrub and herbaceous vegetation associations; and
- (7) water bodies incorporate wetlands, inland wetlands and coastal wetlands.

2.2 Driving forces

The driving factors considered in our research were based on the literature mentioned in Part One, on data availability, and according to their capability of change for agriculture development and urban growth. The selected driving forces represent the most up-to-date available data and include demographic and economic variables (2001 and 2011) (Statistics Portugal, 2011), physical data, and land use regulation variables. These driving forces were selected following the literature and the specific characteristics of the case study. In addition, to reduce redundancies between variables, the Pearson correlation test was estimated between each method selected and between the driving forces. If the correlation coefficient between the two variables was higher than or equal to 0.9, then one of the driving forces respectively was removed (Griffith et al., 2000). Moreover, we estimated the Variance Inflation Factor (VIF) to measure the inflated variance (Brien, 2007).

Table 4.5 identifies the list of driving forces, used in each method, to explain LUCC and agricultural land fragmentation. The reference period of the data, the original scale, and the data source were also showed.

Table 4.5 – Driving forces used in each method: 0. Land use/cover; 1. demographic and economic; 2. physical elements; and 3. land use regulation (method: ABM – agent-based model; AF – agricultural land fragmentation; ANN – artificial neural network; and CA – cellular automata).

Category	Driving force	Year	Method	Original scale	Source
0	Land use/cover	1995; 2010	ABM, AF, ANN, CA	1:25,000	COS/DGT
1	Population density	2001; 2011	AF, ANN, CA	Statistical subsection	Statistics Portugal
	Dwellings		AF, ANN		
	Buildings		AF, ANN		
	Population of farmers	1999; 2009	AF	Parish	
	Agricultural Area Used		AF		
	Average urban land price (m^2)	February 2017	ANN	Parish	imovirtual.pt
2	Distance to the road network	2017	ABM, AF, ANN, CA	1:10,000	OpenStreetMap
	Distance to urban areas	2010	ABM, ANN, CA	1:25,000	COS/DGT
	Distance to agricultural land		ABM, CA		
	Distance to coastline	2018	CA		DGT
	Distance to hydrographic network	2002	CA		Igeoe
	Slope	---------	ABM, AF, ANN, CA		
3	National Agricultural Reserve	2014	AF, ANN, CA	1:25,000	PDM
	National Ecological Reserve		AF, ANN, CA		
	Non-aedificandi areas		ABM, AF, ANN, CA		
	Urbanizable areas		AF, ANN, CA		

The demographic and economic drivers were obtained through Portuguese census and the periods are the closest to the time-period available for the land-use data. Population density, dwellings, and buildings have a positive effect on urban growth (Triantakonstantis and Mountrakis, 2012). The population of farmers and agricultural area used are directly related to the agricultural land increase or decrease. The higher the values of these driving forces, the higher the cultivated areas will be registered (Sima et al., 2015). The average urban land price (m^2), as discussed in previous chapters, reveals that the higher the value, the higher is the probability of land to be converted into urban development (Ettema et al., 2007; Koomen et al., 2007).

Concerning the physical elements, distance to road network is identified as a vital driver in land-use conversion from non-artificial surfaces to artificial surfaces (Stanilov, 2003). The proximity of road-network to agricultural land also encourages agricultural development, taking into account the consumers' proximity. In addition, road network is an indicator of urban pressure (Triantakonstantis and Mountrakis, 2012), in which urban growth frequently occur near transportation facilities (e.g., road-network intersections), determining its form and structure (Rui and Ban, 2011). Regarding the distance to urban area, there are currently in spatial planning, the concern of build new urban areas close to existing urban areas (Veerbeek et al., 2010), due environmental, demographic, social and economic reasons (Alonso, 1964; Leão et al., 2004b; Megahed et al., 2015; Wu, 2002). Distance to agricultural land is related to the reduction of production costs. As much closer is the agricultural area to another agricultural land-use class, less will be the costs. The distance to the coastline represents the suitability areas for agricultural productivity, in which as closer agricultural land is to the coastal area better for agricultural productivity. Since these areas have frequently mild temperatures, near absence of frost, high air humidity, and low thermal amplitudes (IPMA, 2019). Regarding the distance to hydrographic network, it is related to water availability for agricultural irrigation (Bekchanovet et al., 2010), and for agricultural productivity improvement (Satterthwaite et al., 2010). Furthermore, slope is expressed by percentage or degrees and corresponds to the ratio between horizontal distance and vertical fall. The terrain is an essential physical element that has a strong influence on agriculture viability and urban development. The slope can be a physical limitation for agriculture (Zhang et al., 2007), and a barrier for urban development (Li and Yeh, 2000; Simone et al., 2004; Triantakonstantis and Mountrakis, 2012).

Finally, regarding the land use regulation, indicates land restrictions and promotes specific land uses. The selected driving forces for this category were National Agricultural Reserve (RAN), National Ecological Reserve (REN), Non-aedificandi areas (NA), and Urbanizable areas (UA). RAN corresponds to the areas with high suitability for agriculture practice (Larsson, 2006). It protects agricultural areas of being converted to other uses. REN preserves the natural values, with ecological value and areas with susceptibility to geological erosion (Vergílio and Calado, 2014). Its regulation reduces the impact of urban pressure (Azócar et al., 2007; Sims, 2014). NA is the restriction for urban development. It includes Natura 2000. Made up of Special Areas of Conservation and Special Protection Areas, it preserves vulnerable habitats and species and ensure that these areas are restored and maintained in proper conservation (EC, 2015). And UA defines the best areas for new built-up areas, and they are regulated as areas expected to be urbanised within the next ten years.

Different normalisation methods are used to combine data in the same unit scale such as fuzzy logic (Jiang and Eastman, 2000; Zadeh, 1965), multi-label classification (Omrani et al., 2017), Z-score (Altman, 1968), and min-max (Jain et al., 2005). In our study, we choose a sigmoidal fuzzy membership functions (Chen & Wang, 1999) to data normalization, due to its interpretability and simplicity (Rodríguez-Fdez et al., 2016), and its ability to deal with uncertainty, incomplete data, and nonlinearity (Bauer and Tomizuka, 1996; Zimmermann, 2010). In fuzzy logic, the values range from 0 to 1, with 0 being no suitability and 1 is the highest suitability (Fig. 4.6).

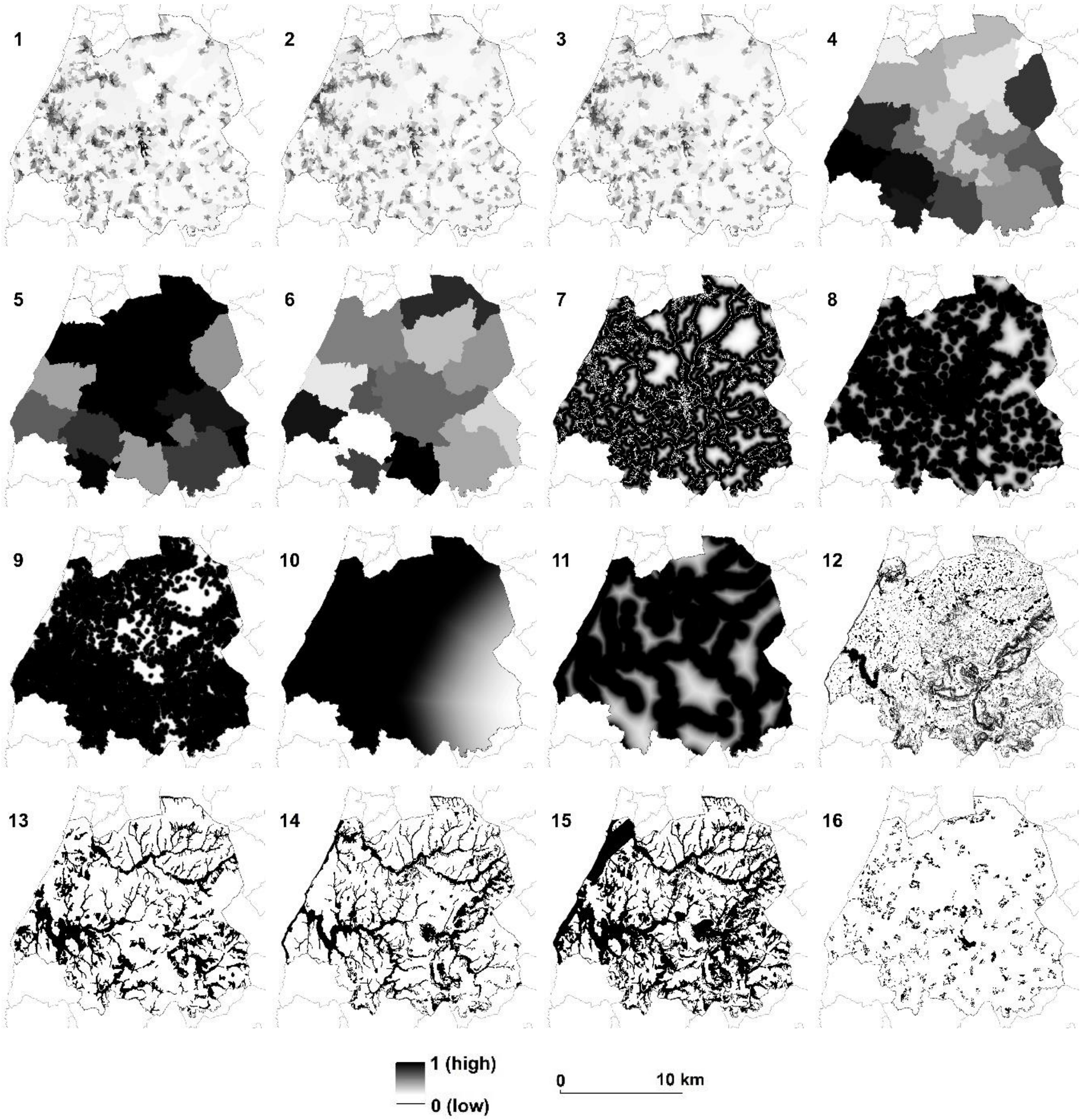

Figure 4.6 – Driving forces. 1. Population density; 2. Dwellings; 3. Buildings; 4. Population of farmers; 5. Agricultural areas used; 6. Average urban land (m^2); 7. Distance to road network; 8. Distance to urban areas; 9. Distance to agricultural land; 10. Distance to coastline; 11. Distance to hydrographic network; 12. Slope; 13. National agricultural reserve; 14. National ecological reserve; 15. Non-aedificandi areas; 16. Urbanizable areas.

Conclusion Chapter 4

This chapter describes the case study and data acquiring and management. Torres Vedras Municipality (Portugal) was selected for the experiments of this research.

In the first section of this chapter, we characterised the case study regarding the geographic, demographic and economic situation, and the land use and driving forces used in the different methods were shown.

In the second section, we introduced the data management, in which we explained some pre-processing of geospatial data such as GIS data attributes, data standardisation, and multicollinearity.

In the next chapter, we will introduce the methodological procedures to measure the influence of urban growth on agricultural land-use changes, and a method to analyse agricultural land fragmentation.

Chapter 5 – Measuring agricultural land-use dynamics: the influence of urban growth on agricultural land fragmentation

Introduction Chapter 5

LUCC may take place across a specific landscape over a given period. It can occur naturally or through anthropogenic changes. In this chapter, we will present two different approaches to measure agricultural land use dynamics. One measuring the influence of urban growth on agricultural land variation and fragmentation, and another method used to measure agricultural land fragmentation using a coupled approach of landscape metrics and cluster analysis. In both methods, we identified the land conversion impacts on agricultural land.

1. The influence of urban growth in agricultural land use patterns

Urban growth is responsible for changes in agricultural land use patterns, dynamics, and spatial structure. In this section, we conceive and describe a method, which we called Land-use chAnge and Neighbouring Distance—LAND, to measure and estimate the impacts of urban growth on agricultural land.

1.1 LAND method

The purpose of LAND method is to identify the distribution of urban growth in agricultural land dynamics from the edge of existing urban areas. We assessed whether the urban growth trend is more or less discontinuous, and we verified the greater or smaller urban containment. The periods of analysis are between 1995 and 2010 (year 0–year 1). The results achieved were visualised as maps and graphically (Fig. 5.1).

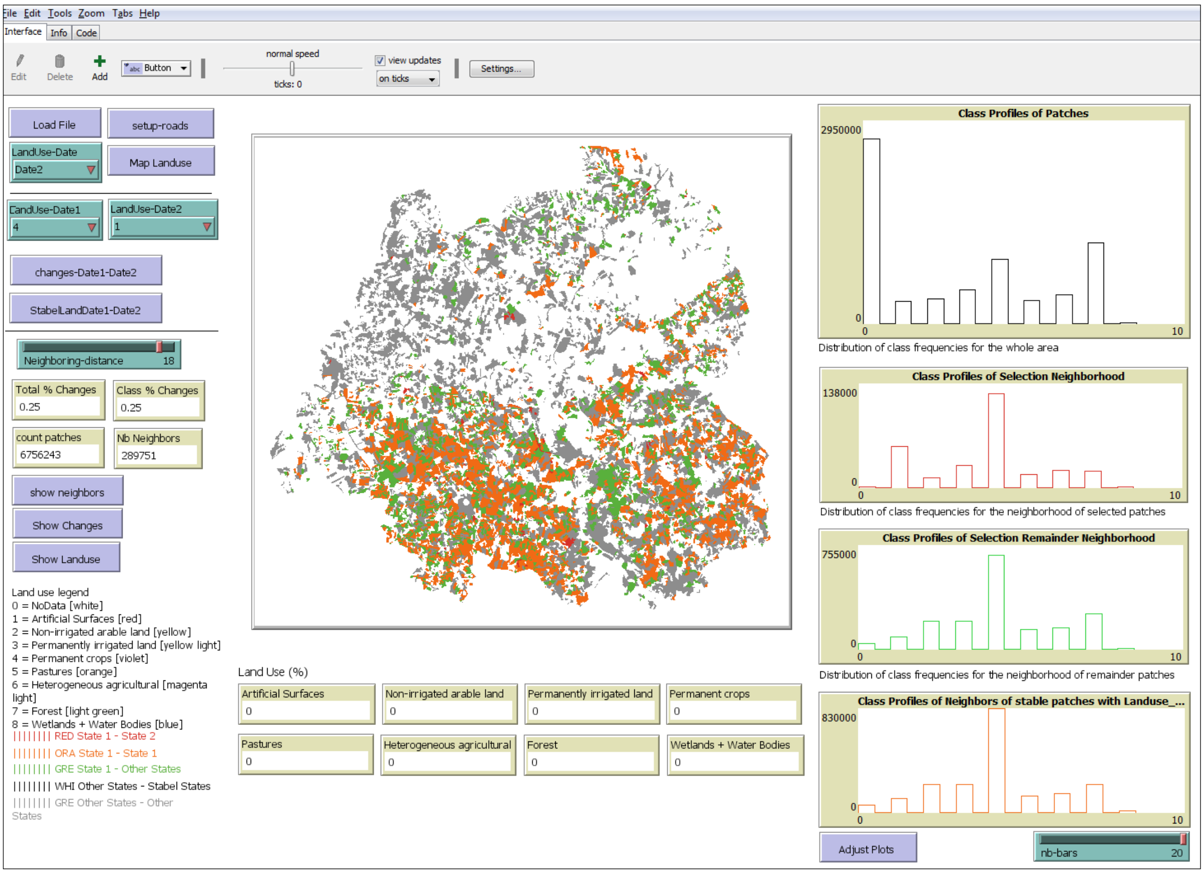

Figure 5.1 – Land-use chAnge and Neighbouring Distance (LAND) method interface. Author: Gomes et al., (2018)

The LAND method was written in the Logo programming language and developed in NetLogo (please see the programming code in Appendix I). NetLogo is one of the most commonly used software tools to model the environment (Banos et al., 2015; Donkin et al., 2017; Tisue and Wilensky, 2004). The LAND method aims:

- quantify LUCC in area (ha) and percentage from year 0 (1995) to year 1 (2010) at different distances, ranging from 10 m to 200 m (we estimated the values for each 10 m section zone), and from the land-use class *x* to the land-use class *y*;
- quantify the impacts of urban growth in the agricultural land and forest;
- identify the distribution of class frequencies for the neighbourhood of remaining (not selected) land use classes; and
- detect stable land use classes between two periods.

In each running process (the step from state 1 to state 2), the LUCC output can be visualised graphically in the interface, and a .txt table. Figure 5.2 illustrates an extract of how the LAND method is represented after each running process, where we can visualise the state of each cell in different colours.

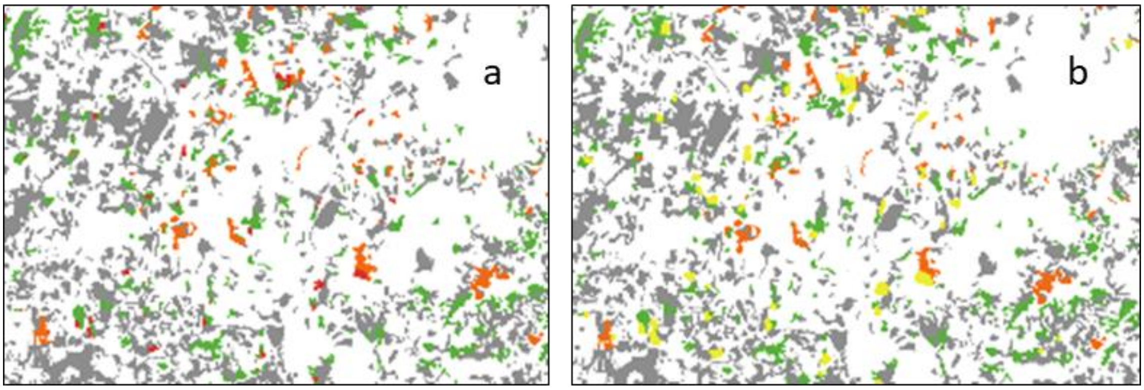

Figure 5.2 – Extract of the LAND method running. (a): LUCC between pastures-1995 (year 0-state 1) and artificial surfaces–2010 (year 1-state 2) (b) Neighbours (50 m distance) in LUCC between pastures-1995 (state 1) and artificial surfaces-2010 (state 2). Each colour represents one state. Red means: changed state 1 to state 2; grey: maintained state 1 as state 1; green: changed state 1 to other states; white: other states that have maintained their class and become stable states; and orange means: changed other states to other states.

In our research, we measured the influence of neighbouring distance for new artificial surfaces (and its impacts on agricultural land) in year 1 counted from the edge of artificial surfaces that had existed in year 0; we then verified in which non-artificial areas of year 0 (non–irrigated arable land, permanently irrigated land, permanent crops, pastures, heterogeneous agricultural land, and forest) these changes had occurred (Fig. 5.3).

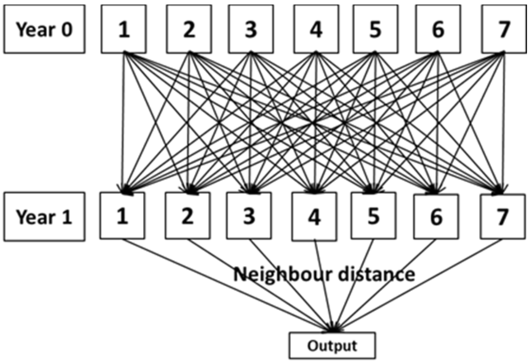

Figure 5.3 – LAND method mechanism.

1.2 Impacts of urban growth on agricultural land

The effects of urban growth on agricultural land have several environmental, demographic, social and economic consequences, already discussed in the previous chapters.

Regarding the land structure, as more compact is the urban growth, less will be the agricultural and forest land fragmentation. Thus, to verify if the new urban areas (in 2010), are more or less compact, from the existing ones (in 1995), we estimated the first goal proposed by LAND method.

So, according to the achieve results we demonstrated the spatial continuity that links the new urban areas with the existing ones and an increasing trend towards the compactness of built-up areas with the 10 m section zone. The spatial relationships between the new artificial surfaces were also tested statistically through the estimation of a linear-log regression, where an r^2 of 0.9864 (strong correlation) was obtained between the distance and the new artificial surfaces. In addition, we tested the spatial autocorrelation analysis using the Moran's–Rook's Case (4 × 4 and 8 × 8 neighbourhood) (Eastman, 2003), in which showed values of 0.9612 and 0.9543, respectively, which indicates that the emergence of new artificial surfaces has a strong spatial correlation with the existing artificial surfaces in 1995. And lastly, the analysis of cumulated values, obtained from LAND method, has shown that 7.6% of the total new artificial surfaces in year 1 (2010) emerged 10 m from the artificial surfaces that had already existed in year 0 (1995); 14.7% at 20 m; 30.9% at 50 m; and 49.4% in the first 100 m. In the 1995–2007 time period, the highest percentage of new urban areas was found less than 200 m from existing ones, when compared to the 2007–2010 period (72.2% and 64.4%, respectively). However, when we analysed new artificial areas closer to the edge of artificial surfaces that had already existed in year 0, we verify greater urban contiguity in the 2007–2010 period. In the 1995–2007 time period, 32% of new urban areas emerged in the first 50 m of existing urban areas, and 35% in the 2007–2010 period (Fig. 5.4).

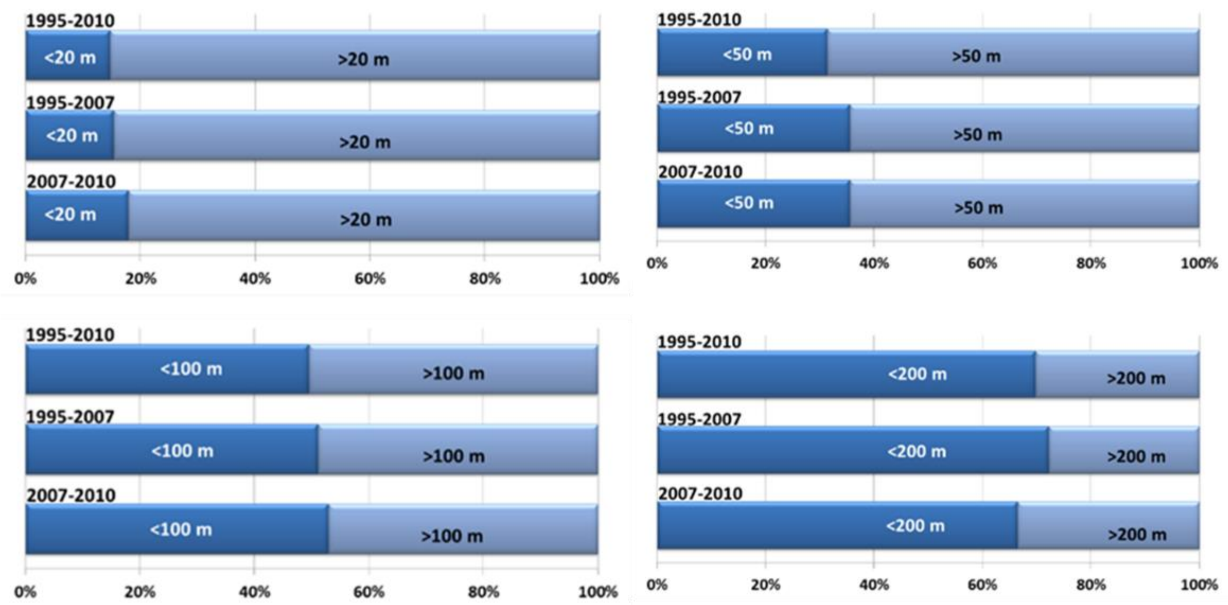

Figure 5.4 – Total weight (%) of new artificial surfaces from the edge of existing urban areas less and more than 20 m, 50 m, 100 m, and 200 m, for the three-time periods: 1995–2010, 1995–2007, and 2007–2010 (data source: (DGT, 1995, 2007, 2010).

Then, to estimate the impacts of built-up areas with the 200 m section zone, we measured the percentage of land use classes that changed from non-artificial surfaces to artificial surfaces at each 10 m interval (from 1995 to 2010). The results reveal that permanently irrigated land lost the highest percentage 200 m from the edge of urban areas (84%), whereas pastures and forest and semi-natural areas lost less land, respectively 60% and 64%, particularly along the urban core of the city of Torres Vedras and along the coastline (Fig. 5.5).

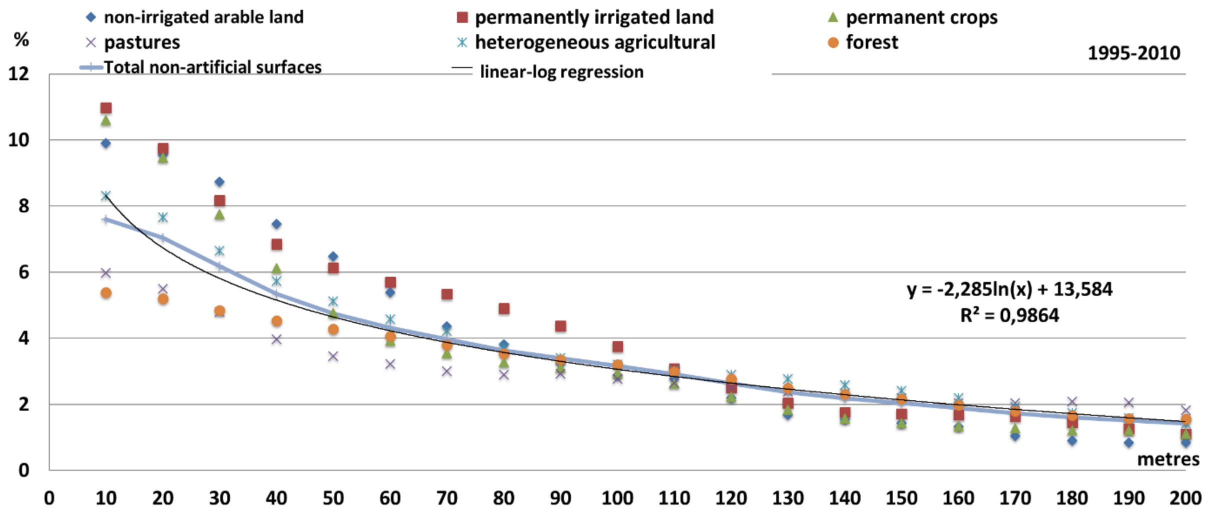

Figure 5.5 – LUCC (in %) from non-artificial surfaces to artificial surfaces, and linear-log regression in the areas of urban growth from 1995 to 2010 according to the distance from existing built-up areas (data source: DGT, 1995, 2010).

Moreover, to verify the impacts of new built-up areas on agricultural and forest land fragmentation in the analysed 200 m section zone, we estimated the patch density index (for 1995 and 2010) of all non-artificial surfaces. This landscape metric is defined as the number of patches divided by the total area, in which smaller values mean more fragmented areas (Schneider and Woodcock, 2008). According to this, Table 5.1 shows these values for 1995 and 2010, in which we verified an increase of land fragmentation in all agricultural land use classes, and in the forest and semi-natural areas, although the compactness of urban growth verified in the same period.

Table 5.1 – Patch density estimated for all agricultural land use classes and forest and semi-natural areas (in the 200 m section zone - from 1995 to 2010) (data source: DGT, 1995, 2010).

Land-use class	1995	2010
2 - Non-irrigated land	0.28	0.14
3 - Permanently irrigated land	0.14	0.07
4 - Permanent crops and heterogeneous agricultural land	0.10	0.07
5 - Pastures	0.31	0.19
6 – Forest and semi-natural areas	0.09	0.03

These performed statistical analysis have led to identifying that between 1995 and 2010, there were progressively less fragmented urban areas, and at the same time an increase in agricultural land fragmentation was verified. We have also demonstrated the high influence of existing artificial surfaces in year 0 on the emergence of new artificial surfaces in year 1. During the 1995–2010 period, 70% of new artificial surfaces appeared in the firsts 200 m from existing artificial surfaces.

A series of authors have studied impacts on LUCC and their implications (Bucała, 2014; Jiang and Tian, 2010; Quintas-Soriano et al., 2016; Wu et al., 2011). Figure 5.6 shows the demographic and land use regulation impacts of urban growth in Torres Vedras Municipality, obtained from the same range used in LAND method. RAN—defined as the best soils for agriculture and imposing a constraint to urban development (Abrantes et al., 2016) —lost a total of 180 ha: 123 ha less than 20 m from existing artificial surfaces and 57 ha more than 200 m from the edge of existing areas. Moreover, we have identified the transgressions to non-aedificandi areas, i.e., areas where construction is forbidden. These non-aedificandi areas include the REN, groundwater, flood areas, railway station, quarries, spring water, cultural heritage, coastal planning, and the Natura 2000 network. We established that a total of 207 ha were consumed by urban development between 1995 and 2010.

Developable areas defined as future urban development in the Master Plan were classified as urban areas between 1995 and 2010, 168 ha less than 200 m, and 56 ha more than 200 m from the edge of existing urban areas (which corresponds to 8.5% of the total developable areas as defined in the Master Plan) (Fig. 5.6).

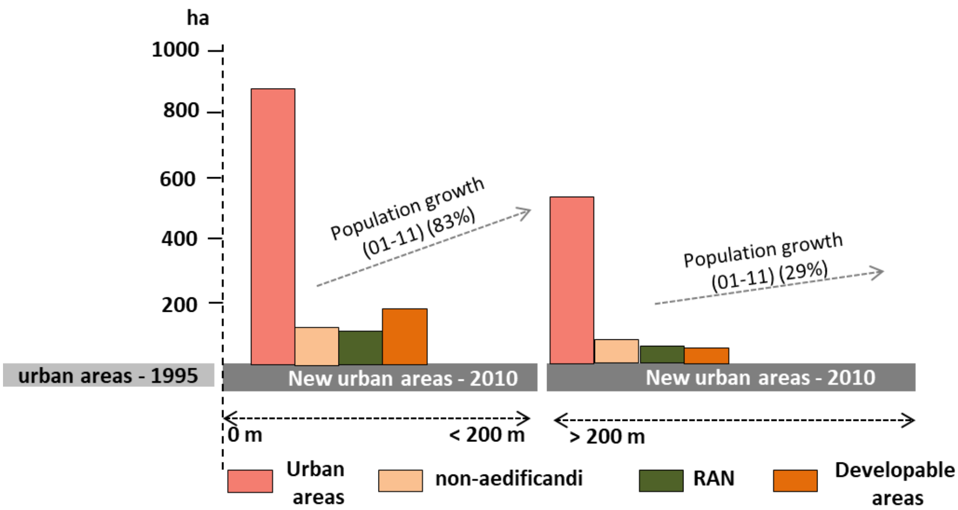

Figure 5.6 – Impacts of urban growth on non-aedificandi areas, RAN, and developable areas.

Comparing the resident population between 2001 and 2011 at subsection level in the urban areas that emerged between 1995 and 2010, we verified that population increased by 83% in the new urban areas less than 200 m from the edge of existing urban areas (in 1995), and 29% in areas more than 200 m away. Lastly, the conversion to urban development led to the decrease of agricultural and forest and semi-natural areas. In the 1989–2009 time period, farmers' population at municipality level decreased from 7,185 in 1989 to 2,201 in 2009, and farms also reduced in number in the same period from 7,245 to 2,337 (Statistics Portugal, 2011).

In the next section, to perform a more detailed analysis of agricultural land fragmentation, we presented a method that couples landscape metrics and cluster analysis.

2. Agricultural land fragmentation

As we verified in the previous section agricultural land fragmentation has increased in the last years in Torres Vedras. Agricultural land fragmentation is characterised by agricultural land uses that are not adjacent to one another; such parcels are small and can be held by the same farmer or by different farmers. The quantification of fragmentation has been used to recognise the land's structural elements and their changes over time (Haase and Nuissl, 2010; Sahraoui et al., 2016; Weng, 2007). Agricultural land fragmentation is a highly vital indicator to monitor landscape quality (O'Neill et al., 1997), and can be employed to create measures aimed at minimising fragmentation (Abrahams et al., 2015), or detecting trends in the evolution of landscape fragmentation (McGarigal et al., 2005).

Agricultural land fragmentation affects the profitability of agriculture but also affects human communities. Recent empirical and theoretical literature has shown the various methods to study this phenomenon. It has been studied using different methods, such as landscape metrics (Gustafson, 1998; Irwin et al., 2007; Leitão et al., 2006; McGarigal and Marks, 1994; Peng et al., 2010; Salvati et al., 2014), regression techniques (Hargis et al., 1998), fractal studies, entropy analysis (Vranken et al., 2014), field research and statistical analysis (Karwat-Woźniak, 2011; Kuemmerle et al., 2009; Vijulie et al., 2012), and econometric models (Jayne and Muyanga, 2012).

Land fragmentation has been widely studied. However, an in-depth analysis aimed at measuring agricultural land fragmentation, and its prediction is needed. The purposes of this section are: (1) to identify different degrees of agricultural land fragmentation (using a set of landscape metrics and a cluster analysis); (2) and to predict agricultural land fragmentation for 2025 using a multi-layer perceptron in a business as usual scenario. Creating agricultural land fragmentation scenarios can be relevant in the decision-making process. Some advantages of applying ANN in the prediction of agricultural land fragmentation are its data-driven and self-adaptive capabilities, the use of universal functional approximations, and the classifiers that do not require initial hypotheses on the data.

These analyses offer insights to land planners so that they can better manage land use classes (and it can be effected in land use regulations) (Li et al., 2016). The innovative approach of this analysis is the fact that it combines landscape metrics and cluster analysis to identify the degrees of agricultural land fragmentation, as well as the use of a neural network to predict its evolution.

2.1 Landscape metrics

Landscape metrics can quantify spatial patterns and structures of land use cover patches (Bhatta et al., 2010; Jaeger and Schwick, 2014; Oueslati et al., 2015). Accordingly, two statistical approaches can be used: first–order and second–order statistics. First-order statistics, e.g., patch area, patch density (Su et al., 2014), number of patches (Torrens, 2006), define the variation at individual locations (Haining et al., 1984). However, second-order statistics identify the spatial dependence between two areas (Getis, 1983), e.g., proximity index (Hargis et al., 1998), nearest neighbour distance (Su et al., 2014), landscape division index (Plexida et al., 2014). According to the recommendation of Farina (1998) to analyse land fragmentation, we need to identify five patch characteristics: patch size, edge, shape, connectivity, and isolation/ proximity. They are effective measures to quantify significant characteristics of agricultural land fragmentation that other landscape metrics are unable to capture successfully. For each patch, we selected those characteristics that better express agricultural land fragmentation according to the landscape metrics more widely used. More specifically: (1) for patch size, we selected mean patch size (MPS) (Su et al., 2014); (2) for edge, we selected mean patch edge (MPE) (McGarigal and Marks, 1994); (3) for shape, we chose mean shape index (MSI) (Su et al., 2014); (4) for connectivity, we selected effective mesh size (MESH) (Su et al., 2014); and (5) for isolation/ proximity, we selected mean proximity (MP) (Hargis et al., 1998). These landscape metrics measure the pattern and structure of each agricultural land use class and indicate the agricultural aggregation or fragmentation level of a given landscape. The more aggregate the patches are, the less fragmented they will be. Table 5.2 describes the characteristics of each landscape metric.

Table 5.2 – Selected landscape metrics.

Landscape metric	Description
MPS	It characterises the extent of fracture of the landscape spatial structure.
MPE	It describes the average edge of land cover patches.
MSI	It indicates the irregularity of patch shape.
MESH	It indicates patch size.
PROX	It divides sparse distributions of small patches.

Agricultural land fragmentation was analysed using landscape metrics that integrated V-Late 2.0 (Vector-based Landscape Analysis Tools Extension) and the FRAGSTATS 4.0 (McGarigal and Marks, 1994) package.

This analysis was performed for 1995 and 2010, for four agricultural land use classes: non-irrigated land, permanent irrigated land, permanent crops and heterogeneous agricultural land, and pastures (Fig. 5.7).

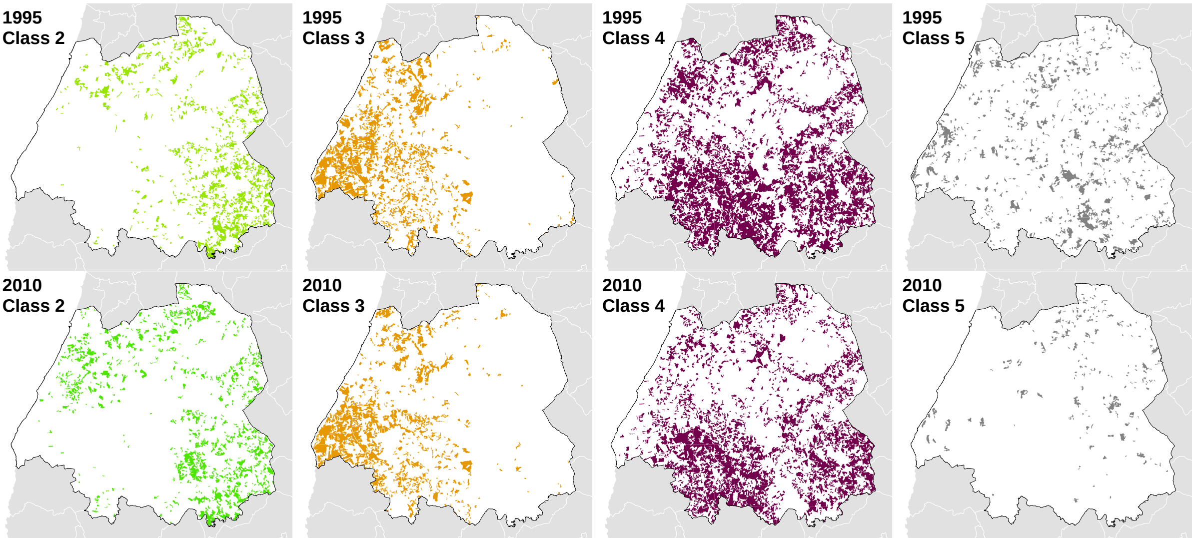

Figure 5.7 – Agricultural land use classes. Land use classes: 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures (data source: DGT, 1995, 2010).

2.2 Driving forces – agricultural land fragmentation

As debated in chapter 1, it was recognized that LUCC is closely related to social, demographic, and economic development (Long et al., 2007; Wu et al., 2013). The relationship between agricultural land fragmentation and human activity is the focus of significant debate in the field of agricultural land use studies (Cheng et al., 2015; Tilman and Lehman, 1987). Based on our results, we believe this to be the case in our study area. In Torres Vedras, during 1995 and 2010, 891 ha of agricultural land have been converted into artificial surfaces. Moreover, forest land has also damaged agricultural land and changed its pattern and levels of fragmentation. In the previous section, we verified a significant correlation between the high levels of agricultural land fragmentation and population/artificial surfaces' growth. This same driver played an essential role in the increase of farmland/agricultural land fragmentation in the studies conducted by Su et al. (2014), Cheng et al. (2015), and Abrantes et al. (2016). The driving forces selected for this analysis are presented in the previous chapter in Table 4.5.

Square of analysis

To better identify the agricultural land fragmentation analysis, as well as to be easier to compare data from different periods, a square of analysis for our case study was performed. However, according to previous studies, land dynamics and driving forces usually change at different spatial scales (Susilo, 2017). Then, we tested two scales of analyses: 2 by 2 km and 5 by 5 km squares (Fig. 5.8).

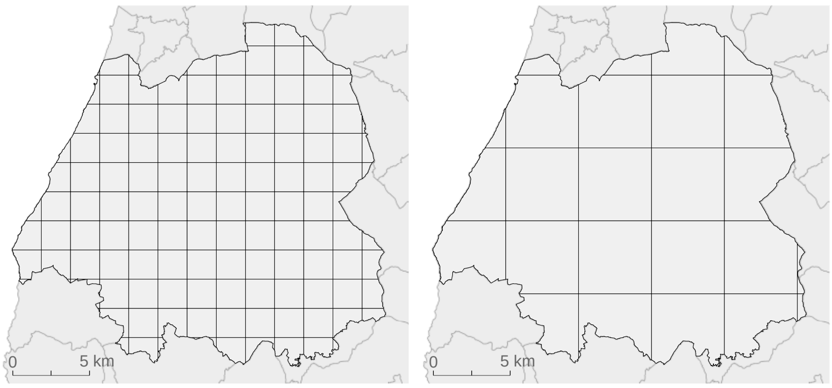

Figure 5.8 – 2*2km (a) and 5*5 km (b) squares.

To aggregate the data of the selected landscape metrics and driving forces (for the analysis of agricultural fragmentation) into these two squares, we estimated three different procedures for each landscape metric and driving force, according to its specific features: (1) density by square; (2) % by square; and (3) average by square. Density by square (1) was estimated according to the proportion of the variable in each square analysed. Each value was estimated pursuant to the value of the variable by parish or subsection divided by the respective area that is concordant with each square. The percentage by square (2) was estimated based on the value of each square divided by the total area of the corresponding square multiplied by 100 to obtain the percentage. Finally, the average by square (3) corresponds to the average value of the variable obtained in each square.

2.3 Multi-regression analysis

Agricultural land fragmentation was analysed by establishing relationships between landscape metrics, land use regulations, environmental, demographic, and economic driving forces. A multi-regression analysis was used to identify the significant driving forces that explain agricultural land fragmentation variability. To verify the outcomes obtained for each analysis (time vs scale), the maximum likelihood method (Lubowski et al., 2008) was used. Also, to verify in which square (2 by 2 km or 5 by 5 km) the dependent variable (representing different degrees of land fragmentation) can be better explained by the driving forces, we computed a linear regression analysis. According to previous studies, land dynamics and driving forces usually change at different spatial scales (Anderson et al., 2009; Roces-Díaz et al., 2018; Susilo, 2017). Smaller cells may suggest better precision, and more detailed information, however, this may not represent better accuracy. Then, we ascertained that for both periods (1995 and 2010) and the landscape fragmentation metrics studied (MPS, MPE, MSI, MESH, and Proximity), the 5 by 5 km square can better explain the driving forces than the 2 by 2 km square, with R^2 value always higher (Table 5.3).

Table 5.3 – R^2 values of linear regression estimated for the 2 by 2 km and 5 by 5 km squares (1995 and 2010) (using as dependent variables the following landscape metrics: MPS, MPE, MSI, MESH, and PROX; and using the driving forces showed in Table 4.5. Land use classes: LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; LUC 5 – pastures) (data source: DGT, 1995, 2010).

	LUC 2				LUC 3				LUC 4				LUC 5			
	1995 2x	1995 5x	2010 2x	2010 5x	1995 2x	1995 5x	2010 2x	2010 5x	1995 2x	1995 5x	2010 2x	2010 5x	1995 2x	1995 5x	2010 2x	2010 5x
MPS	0.78	0.95	0.72	0.87	0.77	0.90	0.78	0.99	0.73	0.98	0.81	0.95	0.85	0.98	0.63	0.90
MPE	0.70	0.89	0.66	0.85	0.77	0.94	0.80	0.99	0.70	0.94	0.75	0.91	0.79	0.97	0.62	0.89
MSI	0.48	0.81	0.43	0.84	0.72	0.86	0.72	0.94	0.60	0.78	0.59	0.89	0.59	0.90	0.52	0.90
MESH	0.83	0.94	0.76	0.88	0.88	0.92	0.85	0.95	0.82	0.96	0.78	0.95	0.86	0.97	0.45	0.95
PROX	0.73	0.94	0.65	0.78	0.69	0.90	0.68	0.95	0.73	0.94	0.63	0.96	0.60	0.92	0.50	1.00

According to these results, we choose the 5 by 5 km square to conduct the subsequent analysis, once they can better explain the selected driving forces.

2.4 Agricultural land fragmentation: 1995 and 2010

As previously mentioned, agricultural land fragmentation is the breaking up of larger areas into smaller and more isolated areas. According to this, to identify similar characteristics in the 5 by 5 km square, a cluster analysis was computed. This technique aimed at identifying different levels of agricultural land fragmentation by grouping landscape metrics. These metrics were normalised using the z-score method and used as variables in *k-means* clustering (cluster analysis) (Milligan and Cooper, 1988). *K-means* clustering is an efficient method to measure the variability of agricultural land fragmentation for the different land-use classes because this method groups data based on proximity in variable space. No spatial constraints or Euclidean distance method were used as parameters. After the first analysis, the MSI metric was excluded due to its low R^2 value in every clustering analysis (below 0.5). R^2 represents how well each variable discriminates the total variation of the dataset (Table 5.4).

Table 5.4 – Overall variable statistics R^2. Land use classes: LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; LUC 5 - pastures (data source: DGT, 1995, 2010).

	LUC 2		LUC 3		LUC 4		LUC 5	
Landscape metrics	**1995**	**2010**	**1995**	**2010**	**1995**	**2010**	**1995**	**2010**
MESH	0.7878	0.9318	0.9662	0.9784	0.7996	0.8893	0.9202	0.5015
MPS	0.7745	0.6643	0.9032	0.9198	0.6751	0.8107	0.7160	0.6792
PROX	0.7679	0.7166	0.9859	0.9814	0.9405	0.8921	0.5035	0.9668
MPE	0.6726	0.5547	0.9178	0.8571	0.6704	0.7430	0.6521	0.6651

The agricultural land use structure and its transition are reflected in the levels of agricultural fragmentation and to support its interpretation. So, clustering analysis was based on three categories: low, medium, and high fragmentation (Fig. 5.9).

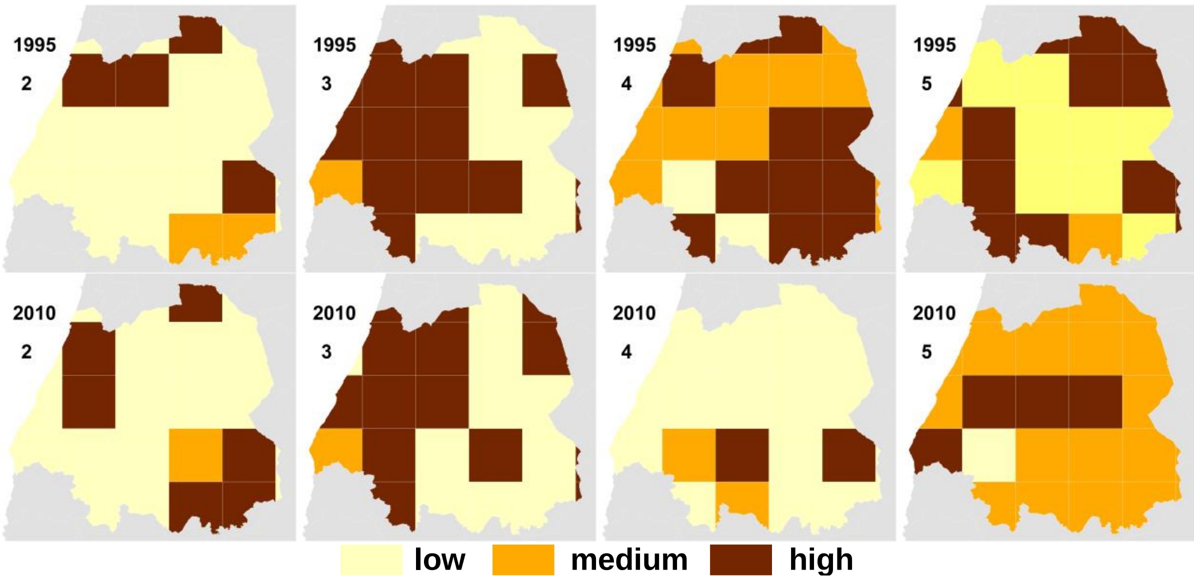

Figure 5.9 – Levels of agricultural fragmentation for 1995 and 2010, using k-means clustering method. Land use classes: 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures.

The cluster "low" highlights the lowest distance between each agricultural land-use class, and conversely, the cluster "high" represents the highest distance between each one.

MESH and PROX landscape metrics had the highest overall R^2 values for every cluster analysis. MESH had the highest values in the cluster "class 2 – 1995" (0.7878), in the "cluster 2 – 2010" (0.9318), and in the "cluster 5 – 1995" (0.9202). Otherwise, PROX landscape had the highest overall R^2 values in the remaining clusters (cluster 3 and 4 for the years 1995 and 2010, and cluster 5 for the year 2010) with R^2 values above 0.89.

Standardised coefficient beta

The landscape metrics were selected as dependent variables, and the variables that reflect demographic, economic and environmental characteristics were selected as independent variables. Using the standardised coefficient beta approach, we determined the most influential driving forces behind agricultural land fragmentation in 1995 and 2010. Standardised coefficient beta is positive when a positive relationship between the dependent and the independent variable is verified. It follows that the most important independent variable in 2010 (cumulative of the five-metrics analysed) in the land-use class 2 and 3 is the agricultural area used (negative relationship), followed in class 4 and 5 by the population of farmers (negative relationship) and agricultural area used (positive relationship) (Appendix II). We demonstrated with these results that the demographic and economic variables we selected explain the process of agricultural land fragmentation in our study area.

2.5 Agricultural land fragmentation: 2025

In this subsection, we evaluated the potential of ANN-MLP to predict agricultural land fragmentation. An ANN-MLP was employed to different levels of agricultural land fragmentation, with a time horizon of 15 years (2025) using the conventional model feedforward backpropagation algorithm (Basu et al., 2015; Snell et al., 2000).

ANN-MLP are capable of taking into account any non-linear relationship among the driving forces and the dependent variable (Mas and Flores, 2008). However, a limitation in the use of ANN-MLP to model agricultural land fragmentation is that this method provides a “black box” approach (Kanungo et al., 2006). In this analysis, the model was based on simple ANN-MLP structure, based on the current conditions (BAU scenario). This analysis is in line with other studies that used ANN-MLP to predict several phenomena, such as LUCC (Morgado et al., 2014), stock market index (Moghaddam et al., 2016), or river flow time series (Hu et al., 2001).

One of the most relevant characteristics of ANN-MLP is the number of neurons in the hidden layer (if they are lacking, the analysis could be poor; conversely, if they are in large numbers, the network may outweigh the data). We opted to achieve an ANN-MLP in automatic mode. The model chooses the parameters to achieve the best performance until the maximum interactions, or maximum accuracy are reached (Ahmed, 2005; Dzieszko, 2014) (Fig. 5.10 and Table 5.5; 5.6).

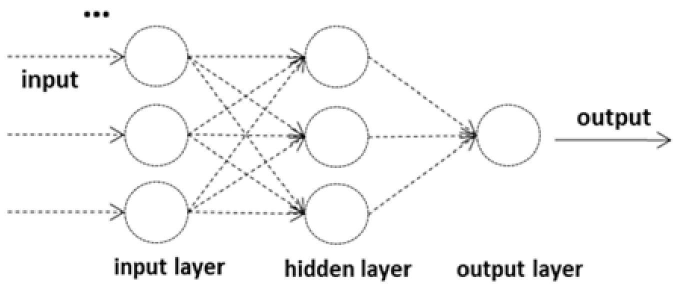

Figure 5.10 – Diagram of a feedforward neural network.

Data were separated into training and testing sets. All the input variables were normalised using the standard deviation method.

Table 5.5 – Network information. Land use classes: LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; LUC 5 - pastures.

Input layer	Covariates	LUC 2	LUC 3	LUC 4	LUC 5
	Number of units	29	29	29	29
	Rescalling method for covariates	normalised			
Hidden Layer	Number of Hidden Layers	1	1	1	1
	Number of Hidden Layers – Layer 1	9	8	6	9
	Activation function	hyperbolic tangent			
Output Layer	Dependent variables	LUC 2 (2010)	LUC 3 (2010)	LUC 4 (2010)	LUC 5 (2010)
	Number of units	2	2	3	3
	Activation function	softmax			
	Error function	cross-entropy			

We used the softmax activation function. It is used to evaluate backpropagation algorithms and is best suited to deal with multi-class classification difficulties. As error function, we used cross-entropy.

Table 5.6 – Network information by land-use class. Land use classes: LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; LUC 5 - pastures.

		LUC 2 (n)	LUC 2 (%)	LUC 3 (n)	LUC 3 (%)	LUC 4 (n)	LUC 4 (%)	LUC 5 (n)	LUC 5 (%)
Sample	**Training**	20	83.3	20	83.3	20	80.0	20	80.0
	Tests	4	16.7	4	16.7	5	20.0	5	20.0
Valid		24	100.0	24	100.0	25	100.0	25	100.0
Excluded		18		18		17		17	
Total		42		42		42		42	

The error is the sum-of-squares while the activation function is applied to the output layer. Table 5.7 shows the cross-entropy error and % of incorrect predictions of the training and testing sets for the four agricultural land use classes analysed. Test results indicate an overall incorrect prediction of 0.345 in Class 2, 0.526 in class 3, 0.829 in class 4, and 1.436 in class 5. This means high prediction levels for all land use classes. This analysis also indicates that the incorrect predictions of agricultural land fragmentation for land use classes 2, 3, and 4 are null, and for class 5 it is 20% (Table 5.7).

Table 5.7 – Model summary of cross-entropy error and incorrect predictions. Land use classes: LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; LUC 5 - pastures.

		LUC 2	LUC 3	LUC 4	LUC 5
Training	Cross-entropy error	6.578	4.656	0.067	4.796
	% of incorrect predictions	10%	5%	0%	10%
Tests	Cross—entropy error	0.345	0.526	0.829	1.436
	% of incorrect predictions	0%	0%	0%	20%

The results obtained with the neuronal network have shown high predictive ability in classifying the levels of agricultural land fragmentation (Fig. 5.11).

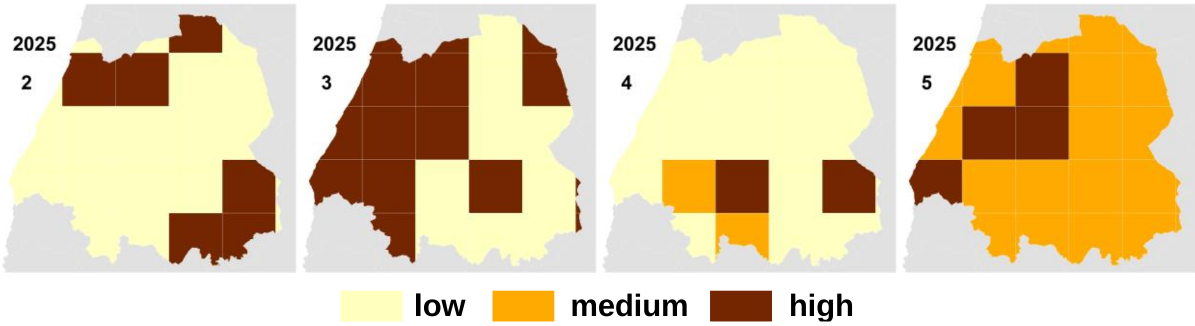

Figure 5.11 – Levels of agricultural fragmentation by agricultural land use class for 2025, using the ANN-MLP method. Land use classes: 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures.

Our results demonstrate that high agricultural land fragmentation areas increased in the permanently irrigated land, and in permanent crops and heterogeneous agricultural land, and the high levels of fragmentation have remained stable in the non-irrigated land and pastures during the reference year 2010 and the projected the year of 2025. In general, results suggest that agricultural land fragmentation will increase in 2025, particularly near the coast (in permanently irrigated land), and in the South of Torres Vedras (in permanent crops and heterogeneous agricultural land) where agricultural land fragmentation is expected to increase (Fig. 5.12).

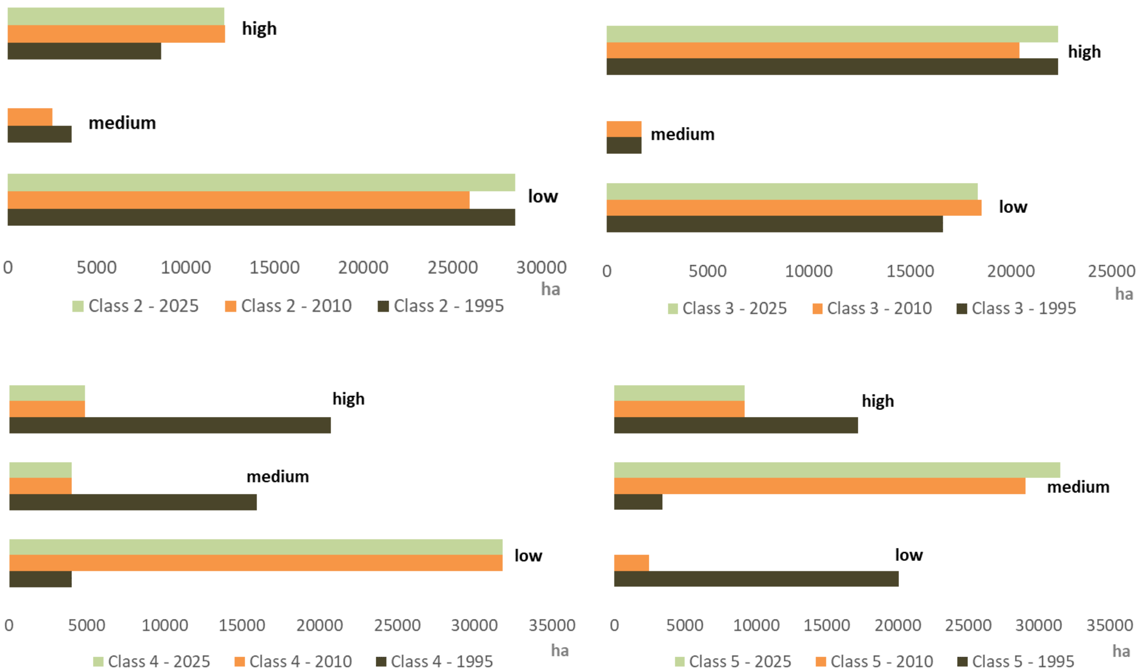

Figure 5.12 – Levels of agricultural land fragmentation by agricultural land use class for 2025, relating the level of fragmentation and the area (in ha) of each agricultural level using ANN-MLP method. Land use classes: 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures.

These outcomes are in accordance with other studies that describe the tendency of agricultural land fragmentation increase in Europe, e.g., Sklenicka (2016), Ciaian et al. (2018), and Hartvigsen (2014).

There are different approaches to validate the achieved results (Marcus and Elias, 1998). One of the most widely used approaches, as found in the literature, is Cramer´s V (Dzieszko, 2014; Wang et al., 2012). Thus, the Cramer´s V value for each agricultural land-use class fragmentation scenario was performed. The validation step aims to determine the accuracy of the predicted map of agricultural land fragmentation in 2025, i.e. ascertaining whether the model is concordant with the real-world (Ahmed et al., 2013; Mondal, Sharma et al., 2016). Using as dependent data land use in 1995, and as independent data the variables listed in Table 4.5, we forecast 2010 agricultural land fragmentation for land classes 2, 3, 4, and 5 using the same ANN-MPL parameters. Agricultural land fragmentation validity was measured by cross-tabulation of the 2010 agricultural land fragmentation with the forecast 2010. Table 5.8 shows the values obtained. These reveal good agreement scores, especially in class 3 (0.9457).

Table 5.8 – Cramer´s V values (LUC 2010, LUC 2010 – predicted). Land use classes: LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; LUC 5 - pastures.

Index	LUC 2	LUC 3	LUC 4	LUC 5
Cramer´s V	0.7145	0.9457	0.6249	0.7427

Conclusion Chapter 5

To measure the spatial configuration, several methods have been studied and used. In this chapter, a method to measure the impact of urban growth on agricultural land use variation was presented, as well a method coupling landscape metrics and cluster analysis to measure agricultural land fragmentation were performed.

Measurements of LUCC can be presented in relative and absolute values (Bhatta et al., 2010). The LAND method, firstly presented in this chapter, was performed at both scales. The main advantage of expressing it at a relative level is that it can be used in different case studies, and the results can be compared. Relating the LAND method with the 13 suitability criteria to measure LUCC, following Jaeger et al. (2010), we can ascertain that the LAND method meets all 13 criteria. These criteria are related to patch structure, and other elements, such as intuitive interpretation, mathematical simplicity, and modest data requirements. The LAND method fails to provide a spatial-geometry analysis, an important issue to measure LUCC (Frenkel and Ashkenazi, 2008; McGarigal and Marks, 1994). However, LAND method, unlike other measures e.g., Pozoukidou and Ntriankos (2017) and Xu and Min (2013), provides detailed information on LUCC in space and in time, offers easy mapping, and shows LUCC monitoring capabilities.

Moreover, the LAND method can be used and adapted for different scales, replicable for other case studies, land use resolution data, and land use classes, and at different neighbouring distances. The LAND method can examine LUCC and land fragmentation from urban, agricultural, and forest land perspective.

In addition, the landscape metrics used in the agricultural land fragmentation analysis have shown they can help understanding landscape patterns. They were used to categorise different degrees of fragmentation (low, medium, and high) and to simulate agricultural land fragmentation in 2025. Our analysis suggests that MESH, MPS, PROX, and MPE landscape metrics are effective measures to quantify significant characteristics of agricultural land fragmentation through different time-periods. The driving forces behind these changes are closely related to demographic and economic development and human activity (Cheng et al., 2015; Tilman and Lehman, 1987) as also demonstrated by Long et al. (2007) and Wu et al. (2013).

By tracking the LUCC between 1995 and 2010, 891 ha of agricultural land was converted into artificial surfaces. We found a significant correlation between the high levels of agricultural land fragmentation and population and artificial surfaces' growth. The same driver played an important role in the increase of agricultural land fragmentation in the studies conducted by Su et al. (2014), Cheng et al. (2015), and Abrantes et al. (2016).

We have confirmed that urban growth had in the studied period consequences in the patterns and dimensions of farmlands, with implications for agricultural productivity (Anriquez and Bonomi, 2007). Understanding the dynamics of agricultural land fragmentation is an essential issue for farms' viability as well as for spatial planning. In this sense, we have introduced in this chapter another method that examined in more detail the agricultural land fragmentation, using landscape metrics and a cluster analyse.

The current tendency, in Torres Vedras, of agricultural land consumption for urban development is contrary to the principles of sustainability. Tracking this evolution is critical. Different policies may have different effects on a territory. Land use planning measures to reduce the loss of agricultural land and protect and preserve natural areas are needed (Bengston and Youn, 2006; Cheshire, 2009; Dawkins and Nelson, 2002). For land planners, the results obtained in both methods can be relevant to identify the impacts of their decisions on landscape transformation at the local level, to define land priorities and designing new policies to avoid undesirable futures. These methods can help decision-makers to develop instruments for implementation of urban containment policies, as well as to limit, monitor, and regulate agricultural land fragmentation, e.g., Bengston and Youn (2006), Dearborn and Gygi, (1993), Fertner et al. (2016), and Jehling et al. (2016) preserve natural and agricultural areas (Bengston and Youn, 2006), and convert vacant plots or redevelop low–density inner-city areas, e.g., Bengston and Youn (2006), Cheshire (2009), and Owusu (2013).

Longer time periods of land use coverage would be an advantage in this work. This would help to check if the land transitions we verified is a long-term or a temporary trend. The results obtained in both methods can also be used as inputs in studies to evaluate the negative and positive impacts of LUCC, such as urban pollution, social fragmentation, water overconsumption, or loss of wildlife habitat.

Conclusion PART TWO

In this Part, we introduced the case study, as well as the data used in this project. In addition, we measured the agricultural land-use changes, identifying the influence of urban growth on agricultural land fragmentation using different methods. According to the results, we verified that agricultural land has been decreasing, and the agricultural land fragmentation has been increasing in our empirical study. We have also presented a methodology towards to understand the agricultural land fragmentation in the future. This methodology was performed according to a BAU scenario to anticipate the impacts on land use, as well as to identify better land-use strategies.

Mapping, measuring and simulating LUCC processes is important to support decision-making and anticipate LUCC transformations. However, we gain in the projection of LUCC if we couple human behaviours with the environment. According to this, in the next chapter, we will illustrate the results obtained from different LUCC methods, in which were integrated farmer's LUCC intentions, captured by interviews.

Part Three: Integrating farmers' intentions and engaging stakeholders' in the LUCC modelling processing

Introduction PART THREE

Part Three Integrating farmers' intentions and engaging stakeholders' in the LUCC modelling processing is divided into two chapters: chapter 6 and chapter 7.

Chapter 6 presents different complex methods to model farmers' LUCC intentions and is subdivided into five sections: 1) the four explorative scenarios; 2) farmers' interviews; 3) modelling farmers' LUCC intentions with CA; 4) modelling farmers' LUCC with ANN-MLP, and; 5) modelling farmers' LUCC intentions with ABM.

Chapter 7 is focused on the analysis of the results and in the participatory workshop. This workshop aimed to engage stakeholders to analyse and to validate the results achieved. Moreover, we have discussed better land-use practices that can be taken, according to each scenario.

Chapter 6 – Farmers’ LUCC Intentions, scenarios, and LUCC models

Introduction Chapter 6

To address the objectives of our study, and test strategies according to the uncertainties of LUCC, we designed four scenarios connected to demographic and economic developments and based on the past and current policies. The time horizon of scenarios is 2025 (usually the ten-year time interval of a master plan). We developed plausible and coherent future pictures, establishing narratives from the present to the thinkable futures. We identified explanations of how the future may be described based on "if-then" or "what-if" scenarios, to support spatial policies which should include better agricultural production management, environment protection, and the best locations for urban development. The four scenarios developed are A0 scenario - BAU; A1 scenario – regional food security; A2 scenario - climate change; and B0 scenario - farming under urban pressure. These scenarios were selected because they incorporate much of the range of potential future impacts on agricultural land and human settlements of our case study. The data used in this analysis included farmers interviews, land use, economic, demographic, physical, and land policies data.

LUCC dynamics is a critical issue in sustainable land use planning (Lambin et al., 2001). The relevance of LUCC in peri-urban land-use planning has been highlighted by many studies (Buxton et al., 2016; Kleemann et al., 2017). Predicting LUCC at the municipal scale is essential to verify areas that are more susceptible to land degradation (Veldkamp and Lambin, 2001).

Models support mathematical representations, simulating its characteristics and behaviours. They are used to develop narratives that can be experienced empirically. Modelling future LUCC provides a relevant mean and its relationship with driving forces (Verburg et al., 2004). An understanding of LUCC is a fundamental part of sustainable land planning. Conversion of agricultural land use classes by human action can affect the natural resource system. Modelling methods have changed the paradigm for LUCC analysis. They have improved the understanding of how driving forces and human behaviours have influenced the LUCC. A diversity of LUCC models have been developed for predicting LUCC at different levels of complexity (Islam et al., 2018; Valbuena et al., 2010a). They consist of three mechanisms: (1) multitemporal; (2) transitional function; and (3) a simulated land use map of LUCC (Batty and Torrens, 2001). CA, ANN, and ABM models have become widespread because of its simplicity to operate, and complexity to simulate phenomena.

Different driving forces were identified in relation to LUCC from 1995 to 2010. A set of factors and constraints that represent the attraction and repulsion for land use conversion were used. The selected variables were mapped for each scenario generated by using common GIS functions. The driving forces were selected following the literature. The farmers' interviews included a set of questions which were used to quantify the land use class conversion.

In this chapter, we presented the narrative of the LUCC scenarios used in this analysis, as well as the results of the farmers' LUCC intentions obtained from the farmers' interviews were shown. Based on this data different LUCC models were used to spatialize the farmers' LUCC intentions. The selected methods were the CA-Markov, ANN-MLP, and ABM. The use of different methods helped to reduce future uncertainties.

1. The four explorative LUCC scenarios

To address the objectives of this chapter and test strategies according to the uncertainties of LUCC, we created four exploratory scenarios connected with demographic and economic developments and based on past and current policies. The time horizon of the scenarios is 2014-2025. We extrapolated plausible and coherent narratives from the present to possible futures to support spatial policies for improved agricultural productivity, environment protection, and the best locations for urban development. We selected four scenarios: A0 scenario – BAU; A1 scenario – regional food security; A2 scenario – climate change; and B0 scenario – farming under pressure. These scenarios are in accordance with the FAO and EU policies trends and challenges and they were the basis to capture the farmers' LUCC intentions in the interviews. Therefore, a transitional probability matrix was obtained for each land-use class in each scenario. These matrices (obtained from the farmers' interviews) coupled with the land use and the selected driving forces identified for each LUCC model (please see Table 4.5) allowed to mapping farmers' LUCC intentions. The flowchart below outlines the scenarios and models used (Fig. 6.1).

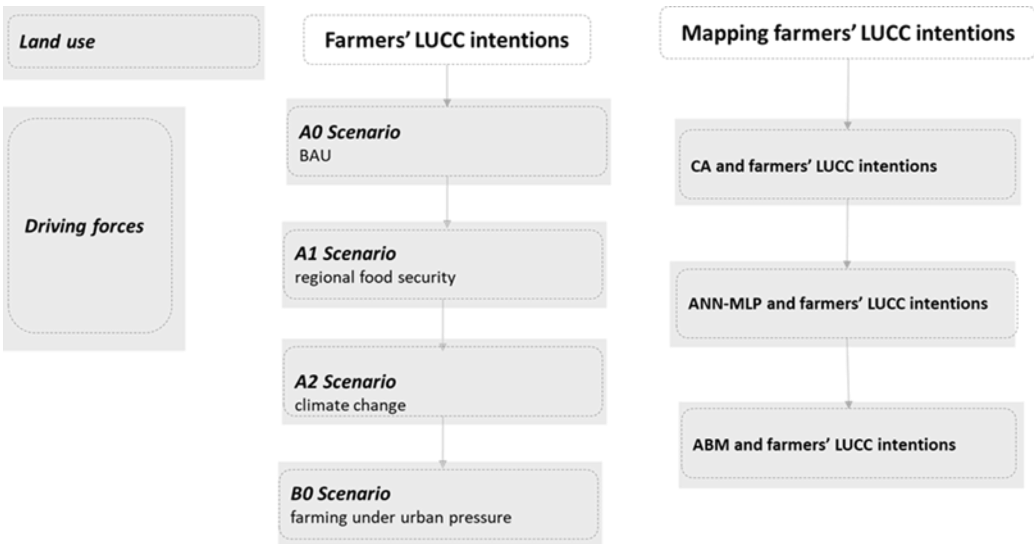

Figure 6.1 – Scenarios and LUCC models applied.

Below we describe the four scenarios developed in detail.

1.1 A0 scenario: BAU

The A0 scenario aims to understand, according to current demographic, social and economic trends, the farmers' LUCC intentions, in which they define their priorities for future agricultural activity (expanding, keeping, or selling their farmland). A0 scenario is also based on LUCC trends observed in the most recent years.

1.2 A1 scenario: regional food security

In the A1 scenario, farmers identify their motivations and priorities in a context of increasing demand for agricultural products, following the guidelines of rural development 2014-2020 and CAP programs. The A1 scenario reflects a reinforcement of local agricultural production, where the average annual work unit of utilised agricultural areas can increase. This scenario includes the valuation of agricultural land, innovative industries, greater use of technology, and the modernisation of agricultural practices (Recanati et al., 2019). To boost agriculture, we highlight the need to improve transportation infrastructure and planning policies to minimise agricultural land fragmentation and conversion (Gomes et al., 2019b). A1 scenario's key trends seek to revitalise agriculture through an increase of European funds. This demand is signalled by a changing food habits (e.g., dietary pattern), and stock building (EC, 2011). The A1 scenario also indicates increased purchasing power and the importance of the agricultural markets closest to urban centres. A1 scenario meets the principle of food security recognized as a priority in the Paris Agreement (United Nations Framework Convention on Climate Change), and the Habitat III Agenda (UN) in which food security of peri-urban regions was identified as a key for a more sustainable urban development. Some of these issues are addressed by the FAO Agricultural Development Economics Division in Alexandratos and Bruinsma (2012).

1.3 A2 scenario: climate change

The A2 scenario describes a narrative in which farmers explain their intentions in a context of declining agricultural production and productivity. In a rapidly declining trajectory, actual production systems collapse as a consequence of climate change. IPCC (Intergovernmental Panel on Climate Change) stated in the latest report that at our case study latitude long periods of drought will be recorded, and this will reduce yields in general. Moreover, several studies have recognized that agricultural production decline when the daytime temperature exceeds a specific value (Luo, 2011; Zhao et al., 2017). Less reliable supplies of water will be also a consequence of climate change, with direct consequences on economic agricultural viability (Günther et al., 2005; von Gunten et al., 2015). Other factors that can also contribute to the production decrease, have been already discussed in several studies such as the increased fuel costs (Lindegaard et al., 2016; Pimentel et al., 1973); ageing farming population (Recanati et al., 2019); farmland fragmentation (Gomes et al., 2019b); increased production costs (Olynk, 2012); and arable land decay (Stoate et al., 2001).

The A2 scenario recognises decreased purchasing power and increased imports of agricultural products from regions where the final cost of agricultural products is lower. Some of these concerns are identified by Anderson (2010) and in The CAP 2014–2020: scenarios for the European agricultural and rural systems by Nazzaro and Marotta (2016).

1.4 B0 scenario: farming under urban pressure

The purpose of the B0 scenario is to assess an increase of built-up areas and an increased probability of new peri-urban residents. The B0 scenario implies population growth; increased purchasing power; increased demand for more living space; growing market demand; and improved road access and public transport facilities. Moreover, in this scenario, real estate is viewed as an attractive investment. These issues are recognised by Satterthwaite et al. (2010) and Rauws and de Roo (2011).

2. Farmers' interviews

Interviews are an efficient and planned format to interpret and describe a phenomenon (Kvale, 1983). In our analysis, they were used to support scenario building, representing an efficient and planned format to interpret and describe a phenomenon (Kvale, 1983). Face-to-face interviews were the technique used to capture the farmers' LUCC intentions. This technique has the advantage of personal interaction (Opdenakker, 2006; Szolnoki and Hoffmann, 2013).

The interviews were designed to investigate farmers' profile, farming practices, and LUCC intentions. They were conducted with currently active farmers. All farmers were informed about the content of this study and gave their consent to participate. Farmer contacts were obtained through local stakeholders such Confederation of Farmers of Portugal, Farmers Association of Torres Vedras, Promotorres, Câmara Municipal de Torres Vedras, and six Civil Parishes: Silveira, União das freguesias de A dos Cunhados e Maceira, Turcifal, Santa Maria, São Pedro e Matacães, Ramalhal, and União das freguesias de Carvoeira e Carmões. In addition, a large number of field visits were conducted to better identify suitable areas for conducting the farmer's interviews (Fig. 6.2).

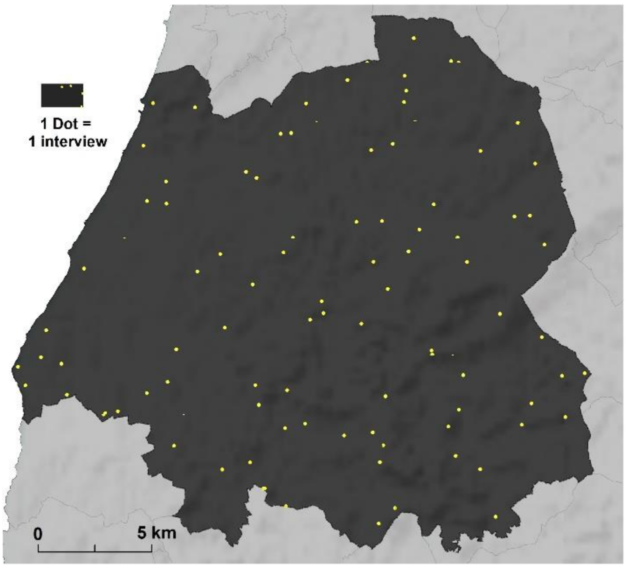

Figure 6.2 – Farmers' interviews (randomly distributed by parish).

Interviews were used and designed to inquire which elements focused on the farmers' profile, farming practices, and farmers' intentions of future LUCC. The farmers' interviews had the following questions: (1) age; (2) gender; (3) education; (4) farmland size; (5) whether the farmer is the owner or the tenant; (6) characterisation of each land-use class of their farmland in percentage. For all scenarios we asked: (7) whether the farmer intends to expand, keep, and/or decrease the farmland; (8) whether the intention is to expand farmland and for which land-use class; (9) the area of intended new farmland, distance from current farmland, and distance to water bodies or hydrographic network (within or outside the Torres Vedras municipality); (10) whether the farmers intended to abandon farming, or decrease farmland size, and if so, how much, for which land-use class; and (11) intentions to change due to other economic activity. Farmers interviews intend to achieve the following goals:

1) What impacts have individual decisions on LUCC?

2) What are the key drivers in the decision of LUCC intentions?

3) What is agriculture's role in urban system development? and

4) How can agriculture be integrated more permanently in the territorial organisation?

Sample, confidence interval, and sampling error

Sampling is an important procedure to capture representativeness (Robinson, 2014). It includes probability sampling (a random selection); purposive sampling (a selective population sample); and no-rule sampling (with no specific rules). To guarantee the representativeness of the population and estimate the sampling errors some probability sampling types such as randomness, stratification, clustering, and systematic sampling was performed.

In our study, probability sampling and stratified sampling techniques were used to select the farmers. Probability sampling was based on a random selection of farmer contacts and in different age groups. Quota sampling improved the representativeness by reducing sampling error (Daniel, 2012). One of the advantages of this technique is the detailed information collected for each subpopulation.

In order to improve data collection, the interviews were conducted over a long period of time. The first stage was carried out in December 2014, and the last stage was carried out in May 2017. To identify a sample of the total farming population to be interviewed in Torres Vedras, we followed different steps. Firstly, to verify data accuracy we estimated the confidence interval and sampling error (Krejcie and Morgan, 1970) (Equation 6.1):

$$n = \frac{N \cdot X^2 \cdot p \cdot (1-p)}{(N-1) \cdot e^2 + X^2 \cdot p \cdot (1-p)} \tag{6.1}$$

where n corresponds to sample size, N = Universe, X^2 = confidence level at one degree of freedom, e = sampling error, and p = sample proportions.

We estimated a sampling factor that corresponded to the ratio between the sample and the farming population (n/N). In our analysis, we divided the total farming population (*N*) into subpopulations ($_k$) N_1, N_2,…,N_k, where the sum of all the subpopulations N_1, + $N_{2\,+}$ …+ N_k must be equal to *N*. We used a sample size in each age group, proportional to its size, where the sizes of the samples are the same.

To identify the sample of the total farming population to be interviewed, we followed the following steps. Firstly, the sample size required for the sensitivity test was estimated using a different margin of error and confidence interval scenarios. In Table 6.1 we illustrate six scenarios.

Table 6.1 – Statistical test and confidence interval scenarios.

Initial Conditions	Margin of error (%)	Confidence level (%)	Population size (n)	Response distribution (%)	Sample size (n)
A1	9.58	95	2.201	50%	100
A2	6.61	95			200
A3	5.26	95			300
B1	10.00	90			66
B2	10.00	95			93
B3	10.00	99			155

In order to assign the margin error and the confidence interval we took into account a balance between 1) the values accepted in the literature (Greenland et al., 2016); 2) the costs per interview; 3) the time took per interview, and; 4) the difficulty of obtaining the farmers' contacts. Following this procedure, we chose the B2 scenario, in which we assigned a confidence interval of 95% and a maximum error margin of 10%. The farmers interviewed by age groups are expressed in Table 6.2.

Table 6.2 – Farmer population (data source: Statistics Portugal, 2009) **and farmers interviewed by age group (Torres Vedras).**

Farmers	Total	15-34	35-64	65+
Farmer population (2009)	2,201	64	1,208	929
Farmers' interviewed	93	10	56	27

Farmers' LUCC intentions

We used 29 variables extracted from the farmer's interviews (Appendix III). Questions included farmers profile (e.g., gender, age, education, and if they are landowners or/and tenants) and farmlands profile (e.g., current farmland dimension and the % occupied by each agricultural land use class). For the A0, A1, A2, and B0 scenario we asked the following questions regarding LUCC's intentions:

- If the farmers intend to expand and/or decrease the agricultural land use classes;
- If they expect to develop and reduce the agricultural land use classes, how much? and where?; and
- if they have the intention to sell their farmland to urban development, if yes, partially or totality?

The responses reveal that 91% of the farmers interviewed are men, and 9% are women. The majority of respondents have between one and four years of education (36%), followed by ten and twelve years (20%), higher education (14%), seven and nine years (17%), and by the population between five and six years of school (13%). The majority of the farmers are landowners representing 90% of the total farmers interviewed. Most farmers have a small to medium-sized farm, in which 47% of their farms have less than 5 hectares, 15% have between 21 and 50 hectares, 9% have between 11 and 20 hectares, 5% have between 6 and 10 hectares, and 2% of farmers have more than 51 hectares.

The findings revealed the farmers' LUCC intentions to expand, keep, and/or decrease the farmland, for which land-use class, and how much for each scenario. Figure 6.3 shows the percentage of farmers' LUCC intentions to expand cultivated land by each scenario and age group.

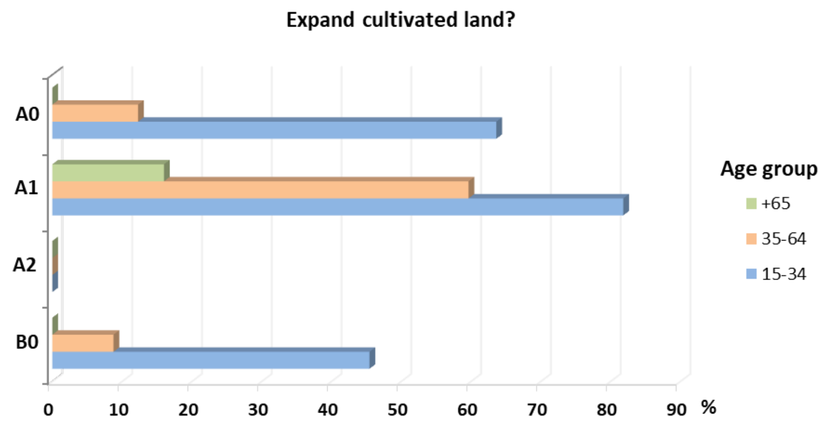

Figure 6.3 – Farmers' LUCC intentions to expand cultivated land (2 – non-irrigated arable land; 3 – permanently irrigated land; and 4 – permanent crops and heterogeneous agricultural land) by scenario and age group.

According to the interviews with farmers, those in the 15-34 age group are the ones that have the highest intentions to expand cultivated land in every scenario, because of their age, and their ambition and capacity to expand their farmland (except for the A2 scenario, in which none of them has the intention to expand cultivated land) (Fig. 6.3).

In detail, and analysing the farmers' LUCC by scenario, in the A0 scenario, 15% of the total farmers in Torres Vedras intend to expand the cultivated land, in which 21% of the farmers intend to expand their cultivated land between 1% and 25%; 29% between 26% and 50%; 29% between 75% and 100%; and 21% more than 100%. Comparing the variation of current farmland size with the A0 scenario, we verify a smooth increase of non-irrigated land (0.06%), followed by permanent crops (10%), and by permanently irrigated and heterogeneous agricultural land (20%). In this scenario, pastureland will register a slight decrease.

In the A1 scenario, 54% of the farmers expect to expand the area of cultivated land. The 35-64 age group shows the greatest intention to increase farmland size. Farmers intend to increase permanent crops by 71%, permanently irrigated and heterogeneous agricultural land by 68%, and non-irrigated arable land by 2.9%.

In the A2 scenario, no farmers intended to expand their cultivated land. However, 30% would decrease cultivated land if the A2 scenario occurred: 29% are in the 15-34 age group; 57% in the 35-64 age group; and 14% are over 65. In this scenario, an increase of pasture land by about 560%, and an increase of forestland by about 281% will occur, with 36% of the farmers intending to reduce their cultivated land between 26% and 50%; 25% between 25 and 50%; 25% between 51% and 75%; and 14% between 1 and 25%.

Lastly, in the B0 scenario, land price valuation exerts a decisive influence. Most farmers are landowners, 84 in a total of 93. They can choose whether to sell or not for urban development (if at present or in the future their land is not affected by restrictions on urban development). While 32% of the landowner farmers intend to abandon agricultural activity, 79% intend to sell their farmland to investors and change their economic activity. The remaining 21% of the farmers intend to sell their farmland partially to investors for residential or tourist uses. However, 18% of these landowner-farmers who intend to sell their farmland (partially or wholly) plan to buy another agricultural land near their current farmland and continue farming. In this scenario, younger farmers (landowners) are more liable to sell their farmland to urban development: 54.5% in the age group 15-34 years; 40.8% of the age group 35-64; and 32% of the older farmers (+65 years).

3. Modelling farmers' LUCC intentions with CA

CA-based on Markov chains are increasingly employed in LUCC (Dezhkamet al. 2017; Sang et al. 2011), incorporating the relationships between land use and driving forces.

The methodology used in this section included the interviews with farmers (which captured the farmers' LUCC intentions), and then a combination of GIS, and CA – Markov Chain – developing step-by-step guidelines towards the creation of a simulation model to predict LUCC. The main contributions of this section are: (a) to spatially analyse and model future LUCC and their impacts on the territory, and (b) to help understand how farmers' decisions can affect the decline, maintenance, or expansion of agricultural land in Torres Vedras.

3.1 CA-Markov

In order to obtain land-use scenarios, based on the CA-Markov model, we used IDRISI Selva software (Eastman, 2012). The simulation scenarios are composed of seven main components: multicollinearity of driving forces, cell states (fuzzy and Boolean logic), neighbourhood configuration, transition rules, time step resolution, and model assessment.

The detailed steps are shown in Figure 6.4.

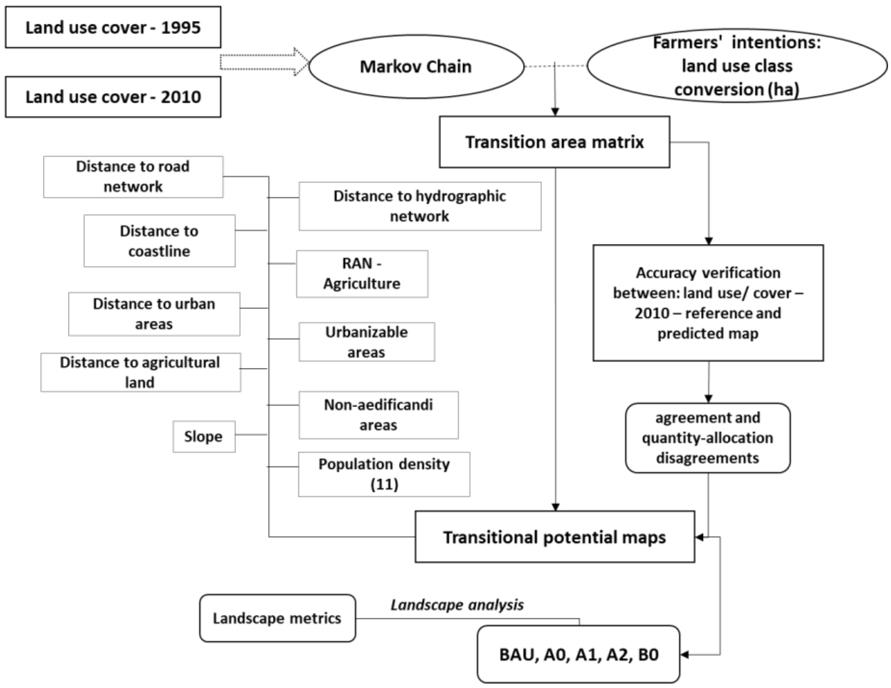

Figure 6.4 – Methodological framework of CA-Markov LUCC model.

Multicollinearity of driving forces

After we identified the most important driving forces that characterise the case study and the phenomena under study, we estimated explanatory variable redundancy (multicollinearity). We used the VIF to quantify the degree of multicollinearity. The values obtained were below 2, which means that all the driving forces in the model are stable (Brien, 2007).

Cell states (fuzzy and Boolean logic)

The fuzzy analysis function was applied to demonstrate the suitability of each cell to be converted from state 1 to state 2. Fuzzy analysis corresponds to a normalisation process in which physical driving forces are transformed into a range of fixed values (Kainz, 2001). In Boolean logic, only two possible values are considered: true or false (e.g., 0 or 1) (Sui, 1992).

Neighbourhood configuration

The neighbourhood configuration chosen was the Moore neighbourhood with 5x5 cells. Neighbourhoods have adjacent cell clusters that define the distance to an individual automaton (Verburg et al., 2004).

Transition rules to quantify land-use class conversion (Markov chain and farmers' LUCC intentions)

To estimate the probability of the quantity of LUCC (in area) in 2025, two approaches were employed: Markov chain and farmers' LUCC intentions.

Markov chain is represented by a set of random driving forces (Diaconis, 2009), and has a matrix of transition probabilities expressed by $t_1 < t_2 ... t_n < t_{n+1}$. Where t_n corresponds to present time, t_{n+1} to a point in the future, and $t_1, t_2 ..., t_{n-1}$ to several points in the past (Basharinet et al. 2004; Levinet et al. 2009).

Farmers' LUCC intentions were collected from the interviews. To obtain the matrix of LUCC, the following procedures were performed:

a) We added the number of hectares of all the agricultural land use classes (non-irrigated arable land, permanently irrigated land, permanent crops and heterogeneous agricultural land, and pastures) that correspond to the current farmlands of the interviewed farmers;

b) We calculated the percentage of growth for each agricultural land-use class (and for each scenario) based on farmers' LUCC intentions;

c) Afterwards, we obtained the percentage of growth and multiplied the percentage of each agricultural land-use class by the corresponding land use class of the reference land use map (to obtain the area in hectares — positive or negative);

d) In order to identify the changes that will occur in the future from each land-use class (transition matrix), we used the trends (in %) of past years (between 1995 and 2010) to obtain positive and negative growth (we distributed the quantity of land according to this %);

e) When the expected growth (in hectares) for a specific agricultural land-use class was higher or lower than the available land (obtained in d), we used the pastures and forest and semi-natural areas as passive land use. We added or subtracted pastures and/or forest and semi-natural areas in hectares (in the transition matrix) if the agricultural area had decreased or increased (proportion distribution between pastures and forest and semi-natural areas was based on the percentage of changes that occurred in the past (1995-2010) using the same procedure described in d);

f) For the B0 scenario, we estimated artificial surface growth as follows:

The area expected to be changed from agricultural, forest and semi-natural areas to artificial surfaces according to the farmers' intentions.

Subsequently, we multiplied the area in hectares of the farmers' intentions to transform their agricultural land into artificial surfaces by the construction index of 0.25 approved in the Torres Vedras Master Plan (Notice No. 927/2014), whose Article 31 specifies the conditions of construction. To identify passive land, we used the same technique described in d) above.

Complying with these two transition rules, we used each technique for the land use classes and scenarios mentioned in Table 6.3.

Table 6.3 – Transition rules techniques used for each land-use class and each scenario.

<table>
<tr><th>Land Use Classes</th><th>BAU</th><th>A0, A1, A2</th><th>B0</th></tr>
<tr><td>Artificial surfaces</td><td rowspan="7">BAU</td><td>BAU</td><td rowspan="5">Farmers' LUCC intentions</td></tr>
<tr><td>Non-irrigated arable land</td><td rowspan="4">Farmers' LUCC intentions</td></tr>
<tr><td>Permanently irrigated land</td></tr>
<tr><td>Permanent crops and heterogeneous agricultural land</td></tr>
<tr><td>Pastures</td></tr>
<tr><td>Forest and semi-natural areas</td><td rowspan="2">BAU</td><td rowspan="2">BAU</td></tr>
<tr><td>Water bodies and wetlands</td></tr>
</table>

Transition potential maps: logistic regression analysis

Logistic regression was used to acquire the relative weights of explanatory driving forces, which represent the very driving forces that influence LUCC (Wu 2002), is estimated according to the following formula (Mahiny and Turner, 2003) (Equation 6.2):

$$P(y = 1|X) = \frac{\exp\ (\sum BX)}{1 + \exp\ (\sum BX)} \qquad (6.2)$$

where P is the probability of the dependent variable; X corresponds the independent variable; B to the estimated parameters.

In each logistic regression analysis, we used different input driving forces to explain the dependent variable (land use/cover 2010). These driving forces depend on each land-use class and scenario. Thus, we used different explanatory driving forces for artificial surfaces (land-use class 1) (AS), agricultural areas (land use classes 2, 3, 4, and 5) (AA), forest and semi-natural areas (land use class 6) (FSNA), and water bodies and wetlands (land-use class 7) (WBW). Table 6.4 shows the driving forces used for each scenario.

Table 6.4 – Explanatory driving forces used in the logistic regression analysis for artificial surfaces, agricultural areas, forest and semi-natural areas, and water bodies and wetlands for each scenario (dependent variable: land use/cover 2010).

N	Driving forces	AS (BAU, A0)	AS (A1, A2, B0)	AA (BAU, A0)	AA (A1, A2, B0)	FSNA (BAU, A0, A1, A2, B0)	WBW (BAU, A0, A1, A2, B0)
1	Distance to the road network	○	○	○	○	○	
2	Distance to coastline	○	○	○	○		
3	Distance to urban areas	○	○				
4	Distance to agricultural land		○	○	○		
5	Slope	○	○	○	○	○	○
6	Distance to hydrographic network			○	○		○
7	RAN			○	○		
8	Urbanizable areas	○	○				
9	Non-aedificandi areas	○	○				
10	Population density	○					

Time step resolution

Time step resolution was 1 year, and the simulations carried out cover a time span of 15 years (or 15-time steps — from 2010 to 2025).

3.2 Testing model performance

Model assessment implies using techniques to check that the simulations are satisfactorily estimated (Trucano et al., 2006). There are many techniques to validate the accuracy of predictions. Kappa index has been widely used to validate LUCC models (Kandziora et al., 2014; Pan et al., 2010; Yu et al., 2011) measuring the inter-rater agreement between categorical variables x and y, and evaluating the prediction performance of classifiers (Cohen, 1960). A kappa of 0 indicates that agreement is due to chance, while a kappa of 1 means a perfect agreement (Viera and Garrett, 2005). However, Pontius and Millones (2011) proposed to quantify disagreement and allocation disagreement.

Different types of kappa coefficients (measuring agreements and quantity-allocation disagreements) were applied to evaluate the simulation performance of different scenarios. We compared simulated 2010 land use with the reference map for 2010. Using the driving forces shown in Table 4.5 (chapter 4, section 2.2) for the BAU scenario, we performed the matrix of Markov transition areas and the suitability obtained from the logistic regression analysis from 1995 to 2007. Subsequently, we computed the CA-Markov to simulate 2010 land use (Fig. 6.5).

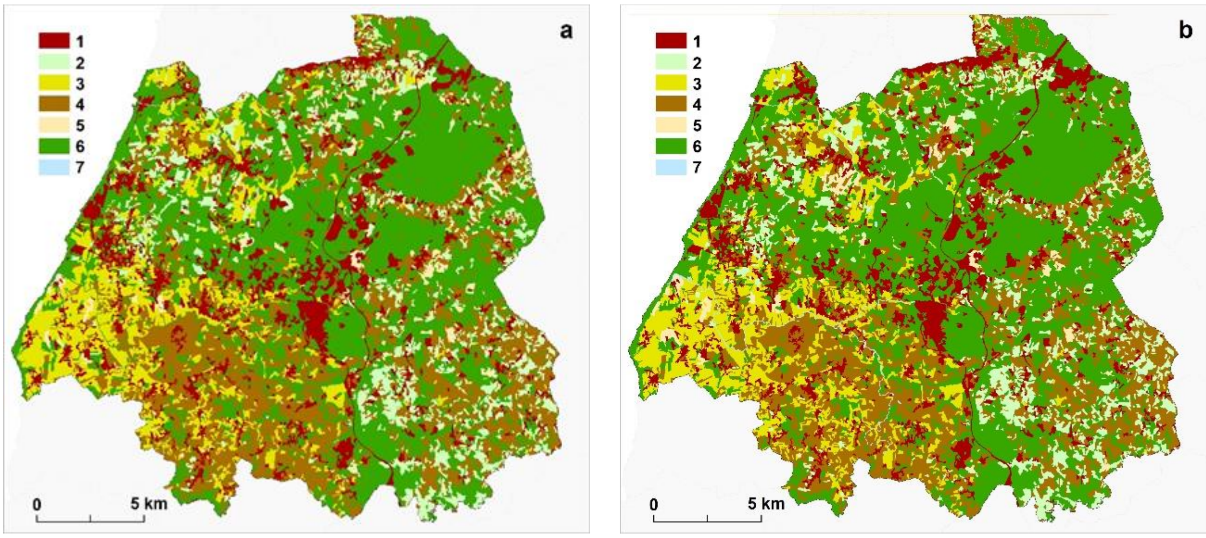

Figure 6.5 – (a) Land use – 2010 (reference map); (b) Land use – 2010 (predicted map). Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2007, 2010).

We measured the inter-rater agreement, i.e., we compared the actual observed agreement with the expected agreement over random allocation. Pontius (2000) refers that kappa values below 1 can be caused both by dissimilarity in sizes and by the allocation of land use classes on the map, and they do not quantify disagreement and allocation disagreement (Pontius and Millones 2011). As the first step to minimise this disadvantage, a contingency table was measured (van Vliet et al. 2011). Table 6.5 represents the cross-tabulation between the reference map and the predicted map for land use in 2010.

Table 6.5 – Cross-tabulation between Land use 2010 - reference map, and Land use 2010 - predicted map (ha). Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2007, 2010).

predicted\ reference	1	2	3	4	5	6	7	Total
1	444478	1644	2575	8977	2664	16229	760	477327
2	1374	291476	17350	34489	7148	9932	66	361835
3	1766	2228	383055	50107	237	17007	144	454544
4	3220	21008	16353	922633	3181	40752	141	1007288
5	977	17349	10215	5180	36611	9453	0	79785
6	12378	36415	18229	34715	38446	1532960	232	1673375
7	0	8	0	0	0	12535	4803	17346
Total	464193	370128	447777	1056101	88287	1638868	6146	4071500

From this contingency table analysis, we retrieve the observed and expected fraction of agreement, and the maximum fraction of agreement (van Vliet et al. 2011). To integrate these parameters into the Kappa index, Hagen (2002) identifies KHistogram and KLocation, described as follows (Equation 6.3):

$$Kappa = \frac{p_o - p_e}{1 - p_e} \rightarrow \begin{Bmatrix} K_{Histo} = \dfrac{p_{Max} - p_e}{1 - p_e} \\ K_{Loc} = \dfrac{p_o - p_e}{p_{Max} - p_e} \end{Bmatrix} \rightarrow Kappa = K_{Histo} \times K_{Loc} \tag{6.3}$$

Where *Po* is the correct observed proportion, *Pe* is the expected fraction of agreement, and *PMax* is the total number of cells taken in by each class. KHistogram ranges from 1, indicating a perfect agreement, to 0 indicating no agreement, whereas KLocation ranges from -1 to 1, in which 1 corresponds to a perfect allocation. Table 6.6 expresses kappa, klocation, and khistogram values obtained between Land use 2010 (reference map) and Land use 2010 (predicted map).

Table 6.6 – Kappa index, kLocation, and KHistogram between Land use 2010 (reference map) and Land use 2010 (predicted map). Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2007, 2010).

Measures	1	2	3	4	5	6	7
Kappa	0.93687	0.77632	0.83023	0.85844	0.42380	0.87465	0.40758
Kappa Location	0.95189	0.78610	0.83729	0.88652	0.44688	0.89028	0.78055
Kappa Histogram	0.98423	0.98755	0.99157	0.96832	0.94835	0.98244	0.52218

The results of the kappa histogram indicate similarity in all land use class sizes (except for water bodies and wetlands); hence, all dissimilarity is caused by the incorrect allocation of LUCC as expressed with Kappa Location.

The indexes mentioned above identify the agreement between two maps. Also, to identify the accuracy of a simulation outcome in relation to the accuracy that can be predictable given the quantity of LUCC in the simulation, three more parameters were estimated: kappa simulation, kappa transition, and kappa transloc. The values obtained are as follows: Kappa simulation = 0.84805; kappa transloc = 0.86703; and KTransition = 0.97811. Since the values are close to 1, this suggests that the predicted map is very accurate. These values were obtained from the Map Comparison Kit (Visser and de Nijs, 2006).

3.3 Logistic regression performance to identify the most significant driving forces

To identify LUCC driving forces and measure the influence of explanatory variables, logistic regression was performed. Table 6.7 describes the driving forces that most influence each land-use class. The drivers that most influence artificial surfaces are those related to human activities (e.g., population density, and distance to urban areas), and for the cultivated land are those related to the distance to agricultural land, physical elements such as distance to the coastline, slope, and agricultural land use protection (RAN). The outcomes present good explanatory capability, which means that LUCC can be explained by these driving forces.

Table 6.7 – Regression analysis for each land-use class. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2007, 2010).

Driving forces	1	2	3	4	5	6	7
Distance to road network	1.2016	0.1138	0.5740	0.3387	-0.1569	0.8147	
Distance to coastline	0.5353	-1.9153	6.4375	-0.6189	-0.0533		
Distance to urban areas	30.0381						
Distance to agricultural land		16.7638	18.9496	18.1329	25.6346		
Slope	0.1782	0.5589	-0.0018	0.2616	-0.2246	1.0069	-0.4155
Distance to hydrographic network		0.1625	0.1776	-0.6626	-0.2194		10.8896
RAN		0.2878	0.8056	0.6006	-0.0544		
Urbanizable areas	-0.8014						
Non-aedificandi areas	1.0200						
Population density	58.0011						

3.4 Land use cover changes in the different scenarios

Evolution: 2010-2025

Every scenario shows an increase in artificial surfaces, particularly the B0. In this scenario, there is an increase by 1,918 hectares (41%) in the place of previously agricultural land, predominantly permanently irrigated land and pastures.

In the A1 scenario (regional food security), substantial growth of permanently irrigated land (3,043 hectares) was seen, which shows the importance that farmers attribute to water availability in their farms (Fig. 6.6).

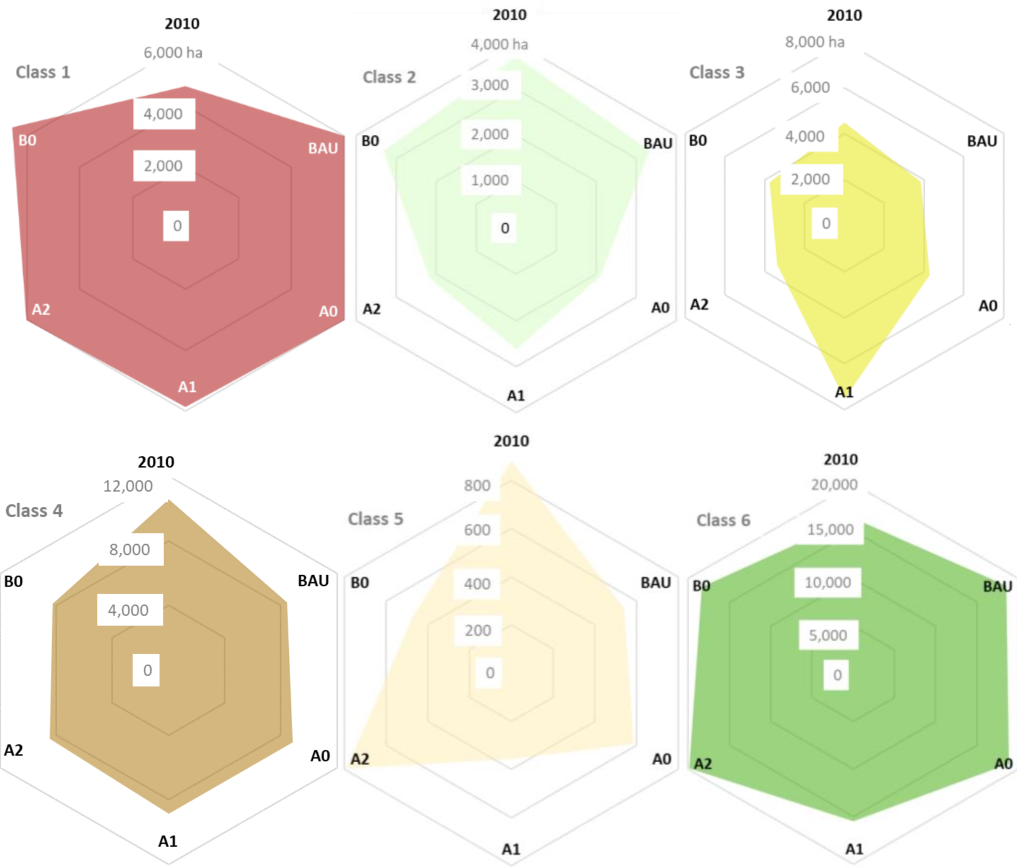

Figure 6.6 – LUCC for each land-use class for the year 2010 and for the 2025 scenarios. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands.

In Figure 6.7, a strong spatial correlation between new artificial surfaces, in the B0 scenario, and their proximity to existing artificial surfaces (in the reference map) can be confirmed, emphasising the relevance of the distance to urban areas driving force for this land-use class.

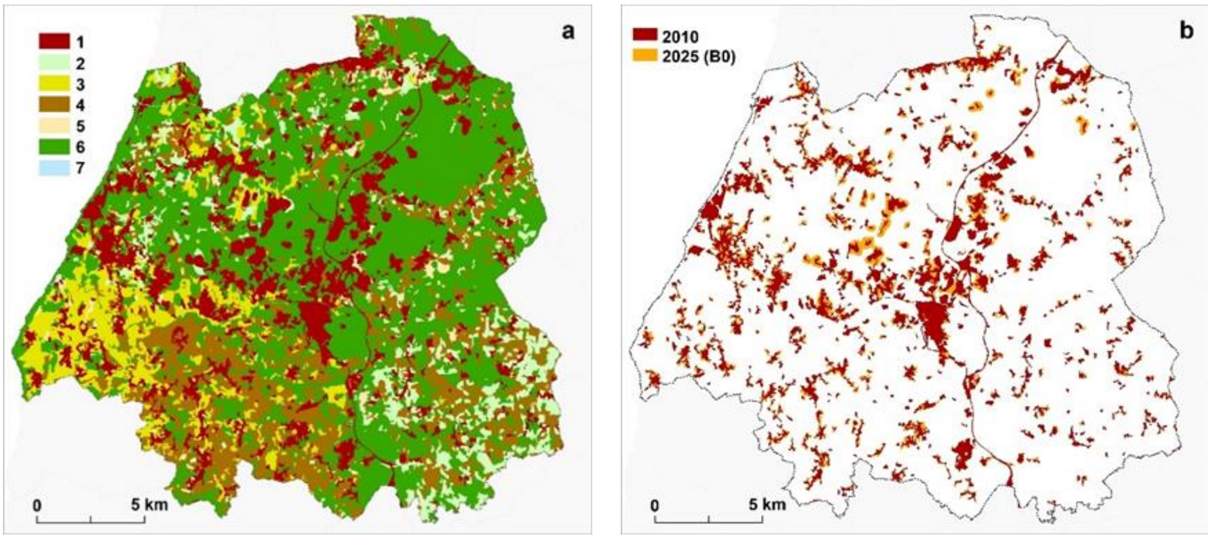

Figure 6.7 – (a) B0 scenario; (b) B0 scenario (artificial surfaces) and Land use 2010 (artificial surfaces) - reference map. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands.

Figure 6.8 shows the best (A1 - regional food security) and worst-case (A2 - climate change) scenarios for agricultural productivity.

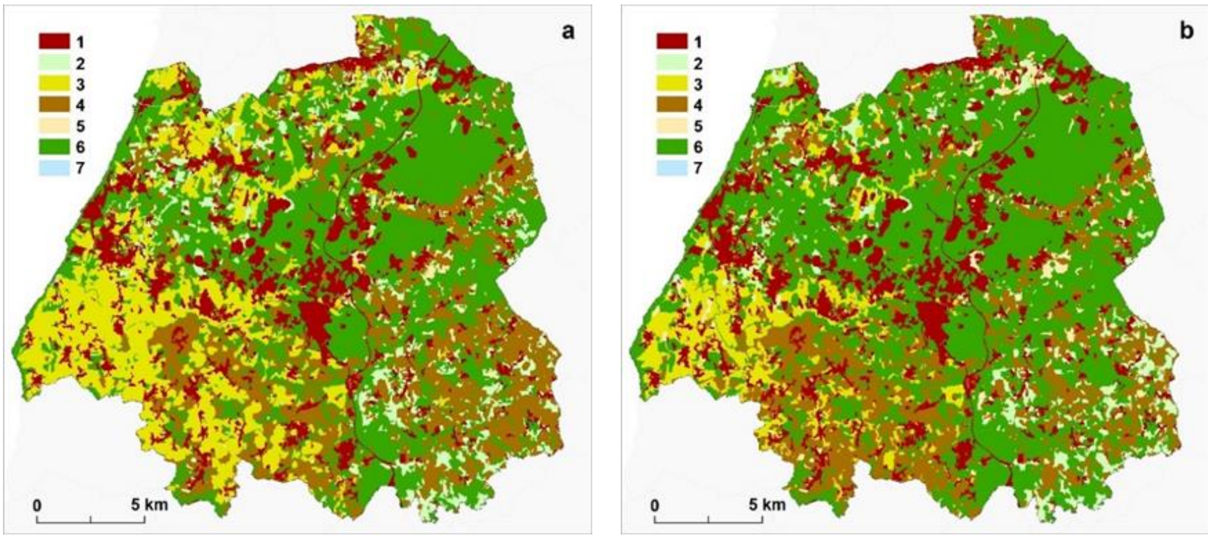

Figure 6.8 – (a) A1 scenario; (b) A2 scenario. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands.

In the A1 scenario, the emergence of new cultivated land is envisaged. We verified an increase by 269 hectares when compared to the reference map for 2010. This new cultivated land from previously uncultivated land was converted from pastures (67%), and from forest and semi-natural areas (33%). This increase was only seen in the permanently irrigated land (Fig. 6.9).

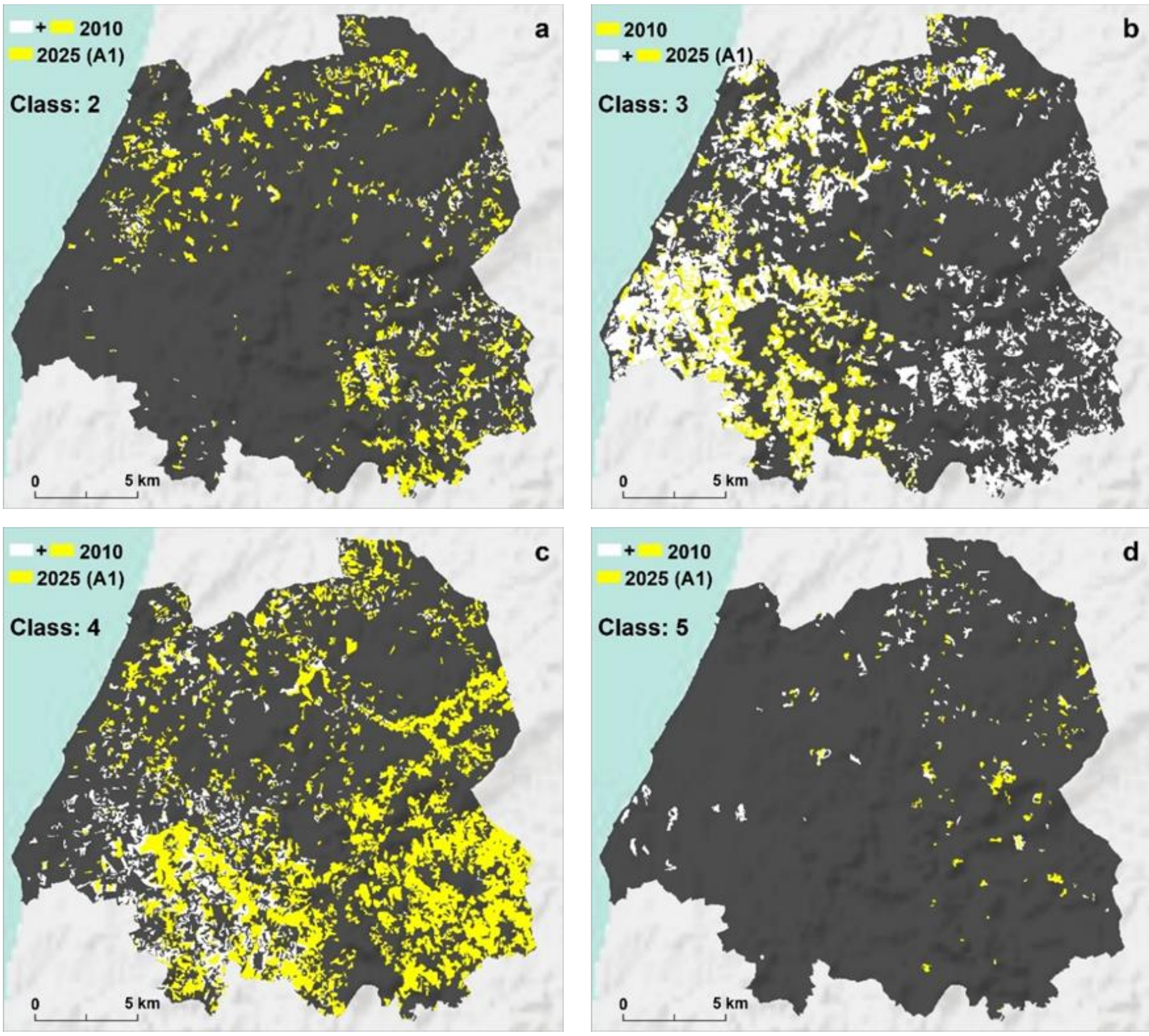

Figure 6.9 – Agricultural land use classes in 2010 (reference map) and 2025 (A1 scenario): (a) non-irrigated land); (b) permanently irrigated land; (c) permanent crops and heterogeneous agricultural land; and (d) pastures.

In the A2 scenario, a loss of agricultural land by 4,743 hectares (from 2010) was registered. The highest losses were recognised in permanent crops and heterogeneous agricultural land, with annual mean losses of 142 hectares, followed by non-irrigated arable land (103 hectares per year), and permanently irrigated land (72 hectares per year) (Fig. 6.10).

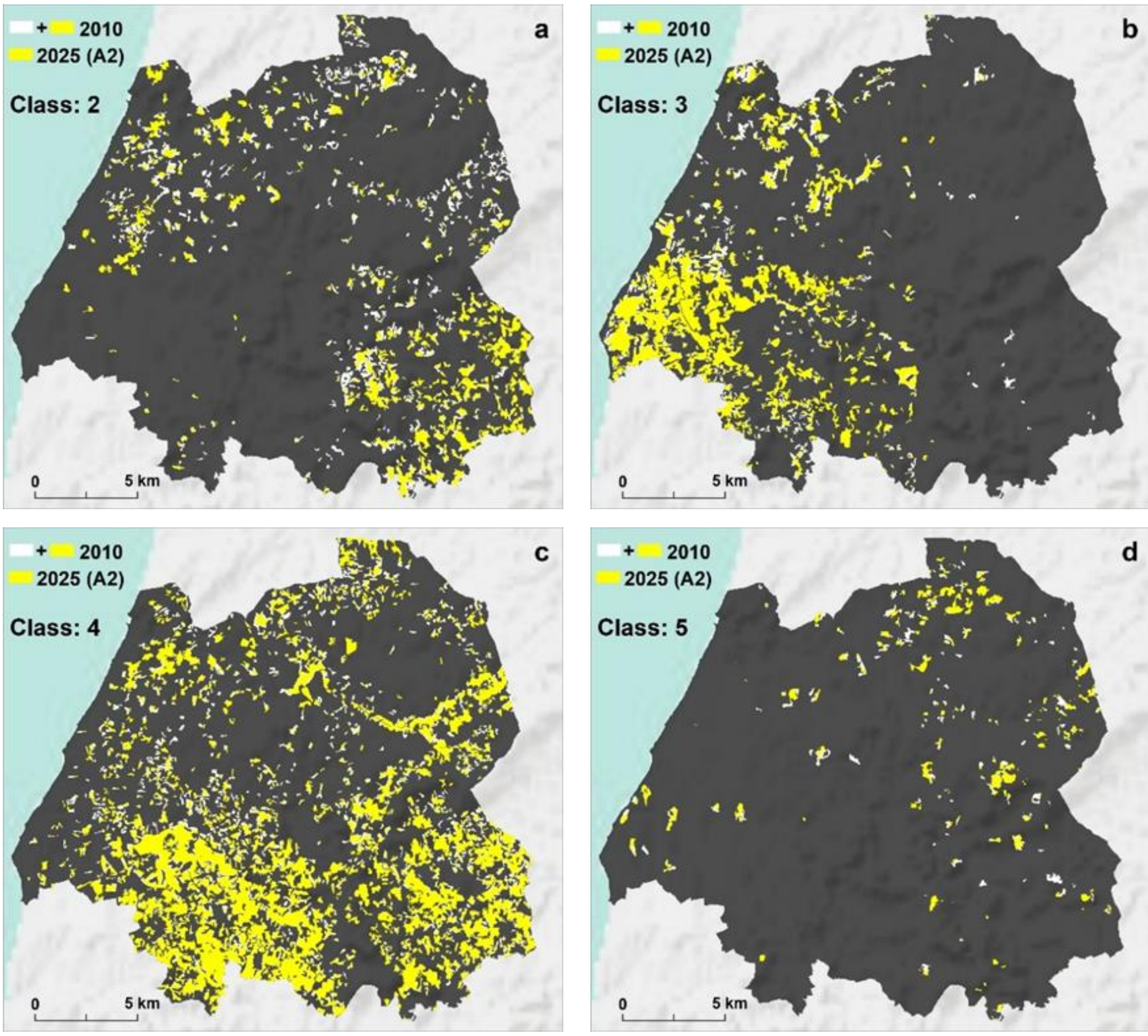

Figure 6.10 – Agricultural land use classes in 2010 (reference map) and 2025 (A2 scenario): (a) non-irrigated land); (b) permanently irrigated land; (c) permanent crops and heterogeneous agricultural land; and (d) pastures.

Figure 6.11 shows the variation of land use classes between 2010 and the 2025 scenarios. Artificial surfaces registered the highest increase in the B0 scenario, the same percentage of increase that had occurred in the past between 1995 and 2010 (41%). In the A1 scenario, permanently irrigated land increased by almost 70% when compared to 2010. Pastures decreased in every scenario — particularly in the A1 scenario — losing 60% of the area. Forest and semi-natural areas gained land in every scenario except for the A1 scenario.

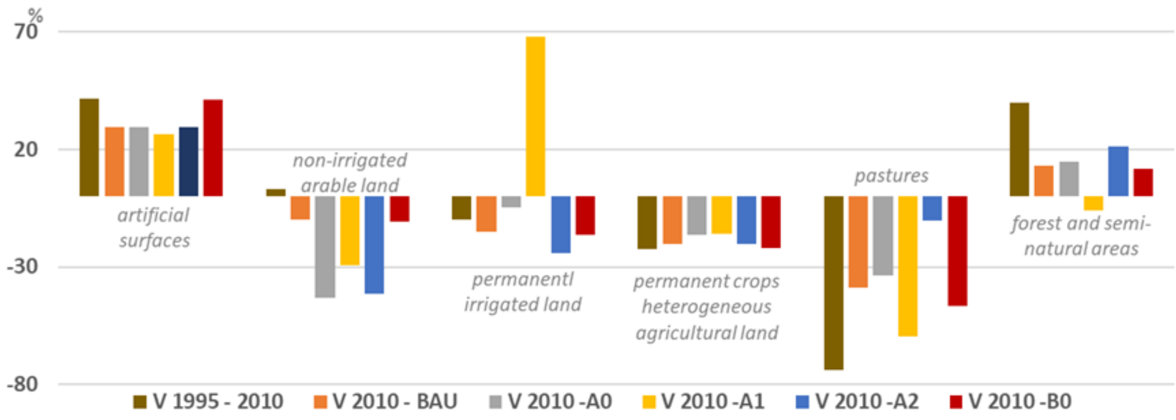

Figure 6.11 - LUCC between Land use 2010 (reference map) and the Land use 2025 scenarios.

Comparing the results obtained in this analysis with the literature review on CA LUCC models, we can state that these results highlight the importance of competition between the various land use classes at the local level, suggesting a self-organising system. These outcomes also address complex problems, such as the evolution of LUCC developed by Hasbani et al. (2011) and Singh et al. (2015).

3.5 Competitive interactions between cells

When CA are used, cell competition arises when two cells with different characteristics oppose each other. This is related to the specific characteristics of land use classes, their capacity and availability to expand to another land-use class, and existing factors and constraints. Therefore, we accordingly compared the percentages of growth that farmers showed in their LUCC intentions with what happened when we modelled these intentions in the CA approach. Table 6.8 shows a comparison between these two evolutions. Regarding the most similar percentages of growth, permanently irrigated land in the A1 scenario had similar growth in both farmers' intentions and the percentage of growth between 2010 and 2025 obtained in the CA simulation (68%). The same happened in the case of non-irrigated arable land in the A2 scenario. Farmers' intentions had a similar percentage of growth for this land-use class (-45.61%) as the results obtained in the CA (-41.57%).

Nevertheless, for one land use to gain land another one must lose it. In the A0 scenario, farmers intended to increase permanent crops and heterogeneous agricultural land by 10%;

however, in the CA simulation, there was a decrease by -16% (for this land-use class) (Table 6.8).

Table 6.8 – Comparison between the evolution of each land-use class according to farmers' intentions and the outcomes obtained in the CA simulation.

Land use classes	A0 (%)		A1 (%)		A2 (%)	
	Farmers' intentions	CA	Farmers' intentions	CA	Farmers' intentions	CA
Non-irrigated arable land	0.06	-43.27	2.90	-29.21	-45.61	-41.57
Permanently irrigated land	20.23	-4.72	67.97	67.96	-17.06	-24.13
Permanent crops and heterogeneous agricultural	10.03	-16.23	71.32	-16.03	-11.00	-20.11
Pastures	-6.35	-33.45	-25.40	-59.67	560.32	-10.31

3.6 Landscape metrics analysis

Lastly, we analysed and assessed the potential consequences of LUCC pattern for each scenario using landscape metrics by comparing the variation and the spatial patterns between the reference map and the predicted scenarios. The mean patch size, the nearest neighbour distance, and the number of patches were estimated. These are the most widely used metrics in landscape analysis (McGarigal and Marks, 1994). The mean patch size metric relates to the size of each land-use class with the number of patches of each land-use class (McGarigal and Marks, 1994). The mean nearest neighbour distance corresponds to the average distance of developed patches to their nearest developed neighbours, based on edge-to-edge distance (McGarigal and Marks, 1994). And the number of patches (McGarigal and Marks, 1994) corresponds to the number of spatial entities. They were estimated assuming that landscape metrics are capable of identifying land-use class morphology (Liu et al. 2008), as well as they are capable to create a dynamic monitoring system of land utilisation. They were estimated for each class and scenario. Following, we described this analysis focusing on the scenarios where we verified the largest spatial variations of LUCC when compared to the reference map (Fig. 6.12):

a) In the A1 scenario, the number of patches in permanently irrigated land dropped from 426 (in 2010) to 292. This reveals the compactness of this land-use class and its expansion concentrated on the same land-use class.

b) In the A2 scenario, in general, agricultural land use classes showed a substantial increase in the number of patches and a decrease in the covered area, revealing an increase of agricultural land fragmentation (Gomes et al., 2019b).

c) In the B0 scenario, the nearest neighbour distance for artificial surfaces was underestimated ranging from 138.86 m (in 2010) to 256.7 m. In addition, the number of patches dropped from 625 in 2010 to 477 in the BAU scenario, and 484 in the B0 scenario, showing more compactness in artificial surfaces (Oueslati et al., 2015).

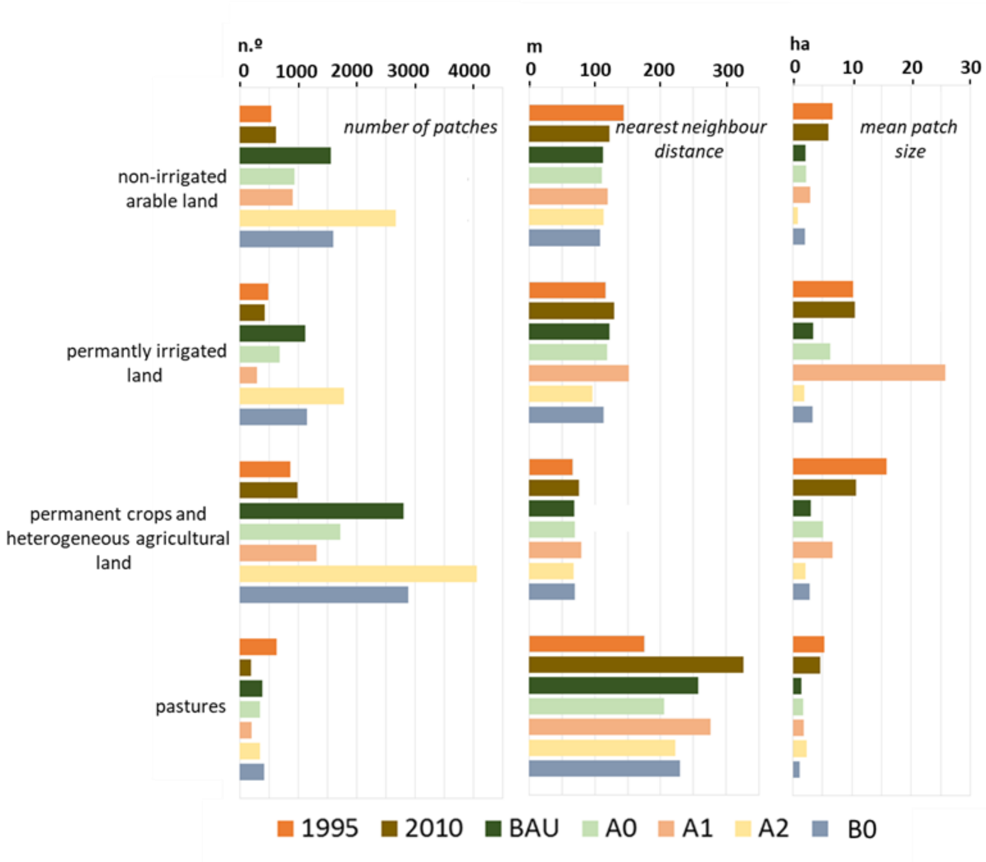

Figure 6.12 – Evolution of mean patch size, nearest neighbour distance, and the number of patches index by reference maps and scenarios.

Additionally, in the BAU scenario (obtained from the CA-Markov LUCC model) we recognised in the permanently irrigated land, and permanent crops and heterogeneous agricultural land an increase in the number of patches and a decrease of mean patch size. This reveals a fragmentation land increase. To reinforce these outcomes, according to the achieved results in Part Two, in the BAU scenario, already discussed in chapter 5 - section 2.5, the agricultural land fragmentation for the same land use classes will also be verified in 2025.

In the next section, we will present another approach based on an ANN-MLP LUCC model (to estimate artificial surfaces growth) and on farmers' LUCC intentions (to estimate agricultural land-use variation) for the same scenarios.

4. Modelling farmers’ LUCC intentions with ANN-MLP

As previously mentioned, decisions about future land use are complex and involve a wide range of conditions. The perceptions, intentions, and interests of the stakeholders involved are usually unpredictable. Different stakeholders manage land by choosing different future options and revealing different visions. Moreover, the use of an algorithm can be decisive in the spatialization of the outcomes. In this sense, in this subsection and to reduce the uncertainties about the LUCC in the future, we explored the same scenarios mentioned above projected for the time horizon of 2025 based on the same farmers’ LUCC intentions. According to this, we modelled an ANN-MLP to allocate the potential areas for urban development.

4.1 Methodological approach

The step-by-step methodology to model farmers’ LUCC intention using the coupled approach (1) farmers’ LUCC intentions (to determine agricultural areas allocation) and the (2) ANN-MLP (to determine artificial surfaces alocation) had the following procedures:

Determining agricultural areas allocation

Firstly, to allocate the agricultural areas: 1. we estimated the variation (%) of the current farmland size and the LUCC farmers’ intentions for each land-use class; 2. we multiplied this variation by the corresponding agricultural land-use class of the reference land use map (2010); and 3. based on land use map (2010) we created a grid divided into cells of 1 hectare. When the variation was negative, we eliminated the cells to other agricultural land use classes until the sum of total losses (in ha) for each agricultural class was calculated. When the expected variation was positive, we used as passive land uses, pastures, other agricultural classes and forest and semi-natural areas (as the land use classes that are available to be converted to other agricultural land use classes). In order to promote consolidation of agricultural areas (Lerman and Cimpoieş, 2006; Liu et al., 2016), we allocated these 1 ha cells close to the same agricultural land use type (in the available area) (Table 6.9).

Table 6.9 – Farmer´ LUCC intentions: variations (ha) of each land-use class – A0, A1, A2, and B0 scenario.

Land use classes	Land use 2010	A0	A1	A2	B0
Non-irrigated arable land	3701	2	107	-1688	11
Permanently irrigated land	4478	906	3043	-764	-782
Permanent crops and heterogeneous agricultural	10561	1059	7532	-1161	-116
Pastures	883	-56	-224	4947	-56

Determining artificial surfaces allocation

To map in the total hectares that each agricultural land-use class could be converted into artificial surfaces, we used the same procedure described above. Here the cells were distributed in the agricultural land use classes (of passive land uses), and the forest and semi-natural areas land-use class.

The prediction to determine artificial surfaces allocation was based on an ANN-MLP. Firstly, we tested several parameters to identify better model performance (Ahmed, 2005; Dzieszko, 2014). The best combination of parameters is depicted in Table 6.10.

Table 6.10 – Network information.

Input layer	Covariates	
	Number of units	14
	Rescalling method for covariates	normalised
Hidden Layer	Number of Hidden Layers	1
	Number of Hidden Layers – Layer 1	10
	Activation function	hyperbolic tangent
Output Layer	Dependent variables	Land use 2010
	Number of units	7
	Activation function	softmax
	Error function	cross-entropy

The ANN-MLP uses three types of layers: input, hidden, and output. Each layer represents nodes which include the lines the flow of information from one node to the next. The input layer is passive (that is, it does not change the data), and the hidden and the output layer are active (the data is changed) (Zou et al., 2009). For the structure of our ANN-MLP, we choose a traditional approach of just one hidden layer. Hard learning tasks can be shortened by growing the number of hidden layers, yet a 3-layer ANN-MLP can compute any decision boundary, changing only the number of hidden neurons (Rocha et al., 2018).

Remembering Kolmogorov's theorem, we know that using 2n + 1 hidden neurons can assure a perfect fit of all continuous functions. Nonetheless, in real-world uses, this can include too many neurons. A solution of 2n/3 hidden neurons gives results with similar accuracy and requiring a smaller amount of training time (Wang, 1994). In our model, ten hidden neurons were used in order to guarantee an equilibrium among accuracy and simulation speed. Considering that several driving forces pointing in the same direction may differ, or that by accumulating enough of them one could exceed the probability of change, we opted for the hyperbolic tangent as first activation (transfer) function.

As dependent variable we used land use data 2010, and as independent variables we used the following driving forces (input layers): land use 1995; population density (2001 and 2011); dwellings (2001 and 2011); buildings (2001 and 2011); average urban land price (2017); distance to the road network; distance to urban areas; slope; national agricultural reserve; national ecological reserve; non-aedificandi areas; and urbanizable areas (please see Table 4.5). As activation function we applied a softmax classifier (Liu et al., 2016), representing a simplification of the sigmoidal function (Chen and Cao, 2009) but performing better when using several land use classes and fitting each input to one class. As error function, a cross-entropy (Nasr et al., 2002) was applied because it was considered more adjusted to evaluate backpropagation algorithms.

Artificial surfaces were allocated following two principles:

1) location according to the ANN-MLP approach for agricultural land where the quantity of growth was based on farmers' intentions to sell to urban developers (1312 ha), and forest land where the quantity of growth was based on the ANN approach (507 ha);
2) since the prediction obtained (in ha) by the ANN-MLP algorithm was lower than the farmers' LUCC intentions, the remaining (in ha) urban growth based on the farmers' intentions to sell agricultural land to urban developers were allocated randomly, in areas without restrictions to urban construction, but following the principle of urban compactness (Burton, 2002; Gomes et al., 2018), as close as possible to the existing urban areas (907 ha). We only illustrated the values of the B0 scenario because in the

A0, A1, and A2 scenario no farmers demonstrated intentions to sell their farmland to urban development.

The most significant driving forces, identified according to the sensitivity analysis, using the ANN-MLP approach, demonstrated that demographic and economic development exerted a significant effect on urban expansion. According to the results obtained, population, buildings and dwellings were the most significant driving factors (Fig. 6.13).

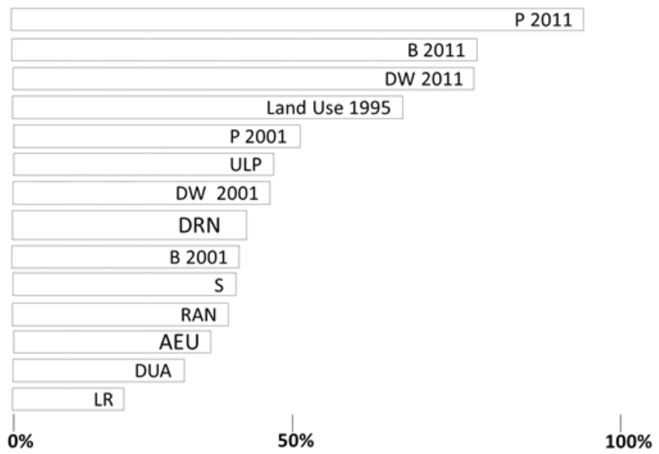

Figure 6.13 – Most significant driving forces (normalised) (%) obtained in the ANN-MLP prediction. Driving forces: population (P); dwelling (DW); building (B); area expected to be urbanized (AEU); distance to road network (DRN); distance to urban areas (DUA); land restrictions (LR); best soils to agriculture (RAN); slope (S); and urban land price (ULP).

4.2 LUCC analysis

Spatial and temporal land-use variation and allocation are desirable for any planning instruments at local, regional and national levels (Hegazy and Kaloop, 2015). Between 1995-2010 under the A0, A1, A2, and B0 scenarios positive and negative change were verified in the different land use classes analysed (Fig. 6.14).

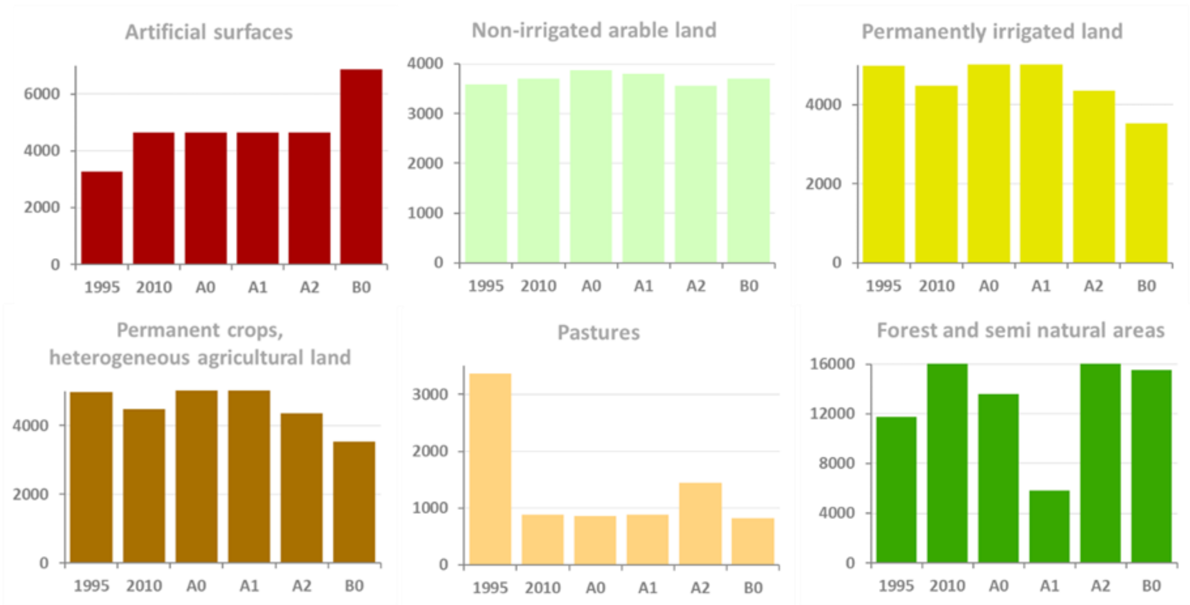

Figure 6.14 – Evolution (in hectares) of each LUC class between 1995, 2010, and 2025 in A0, A1, A2, and B0 scenario.

In the A0 scenario non-irrigated arable land (+5%), permanently irrigated land (+20%), and permanent crops, and heterogeneous agricultural land (+10%) showed an increase in comparison to the reference year of 2010. Nevertheless, pastures decreased by 2%. In the A1 scenario, was also registered an increase in all agricultural land use classes, especially in permanently irrigated land (68%), and permanent crops, and heterogeneous agricultural land (71%). In the A2 scenario, inversely was registered a decrease in all cultivated land use classes, and an increase of 64% in pastures (Fig. 6.15).

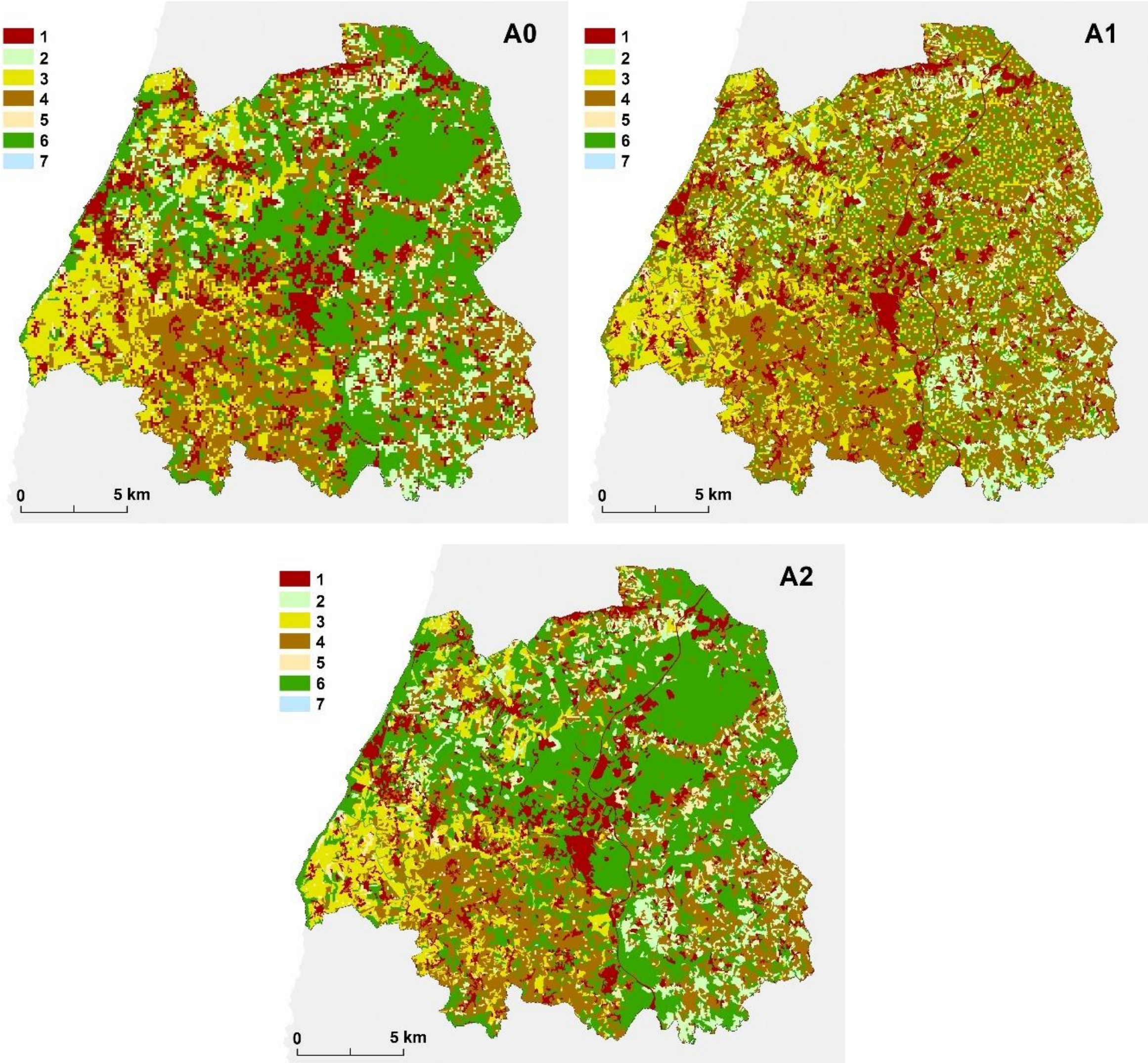

Figure 6.15 – A0, A1, and A2 scenario. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands (data source: DGT, 1995, 2007, 2010).

The B0 scenario showed a decrease in all agricultural land use classes and forest and semi-natural areas, which was converted into urban built-up structures. The urban growth increase of 47.7% (2010-2025), is higher than the growth of 41.5% in the period 1995-2010 (Fig. 6.16).

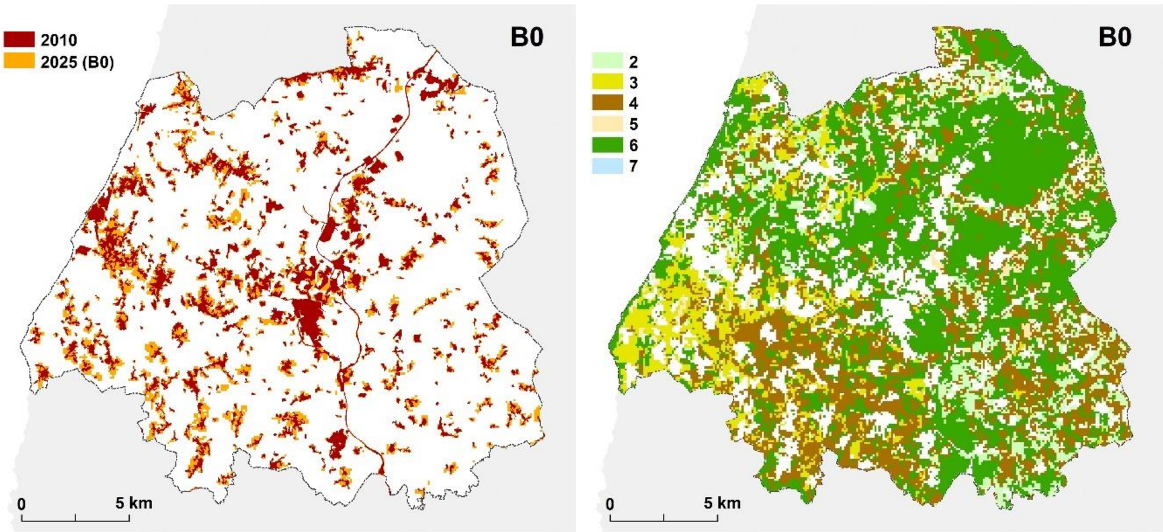

Figure 6.16 – (left) B0 scenario and Land use 2010 (reference map). Land use class: (1) artificial surfaces; (right) B0 scenario. Land use classes: (2) non-irrigated arable land; (3) permanently irrigated land; (4) permanent crops and heterogeneous agricultural land; (5) pastures; (6) forest and semi-natural areas; and (7) water bodies and wetlands.

4.3 Agricultural areas under potential urban pressure

To identify the parishes with the highest potential areas under urban pressure, the driving forces used to predict the artificial surfaces in the previous subheading and a cluster analysis, were computed.

In this methodological stage, four main steps to standardise the data were used:

1) the data were converted at parish level;

2) the density by parish was estimated for the driving forces of population, dwelling, building, area expected to be urbanised, land restrictions and best soils to agriculture;

3) the mean value by parish was estimated for the driving forces of distance to road network, distance to urban areas, urban land price, and slope; and

4) a new driving force was included: the urban growth rate between 1995 and 2010.

To determine the number of clusters, the Pseudo-F statistics method was used. This method relates the between-cluster to the within-cluster sum-of-squares, and a large Pseudo-F statistic specifies different clusters (Caliński and Harabasz, 1974). This analysis was run for 2 to 15 clusters, and the Pseudo-F statistic was estimated for each hypothesis (Fig. 6.17). A peak could be observed at 2-cluster hypothesis.

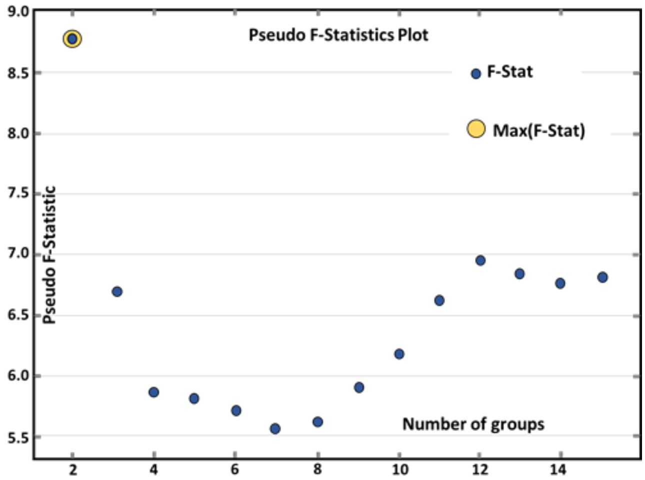

Figure 6.17 – Pseudo F-Statistics value by cluster between 2 and 15.

According to the computed variables and the 2-cluster hypothesis population density (R^2, 0.85), areas expected to be urbanized (R^2 0.64), dwellings (R^2 0.63), buildings (R^2 0.56) and urban growth (R^2 0.55), represent the more effective predictor of clustering (i.e. overall R^2 > 5). Cluster 1 – represents the parishes dominated by the lowest potential intensification of urbanisation, and; cluster 2 – is characterised by the parishes with the highest potential intensification of urbanisation, and where agricultural areas are more vulnerable to being converted to urban uses.

Following in Figure 6.18, we verified the concordance between the parishes of cluster 2, and the parishes where the urban growth was highest, using the coupled method farmers' intentions and ANN-MLP approach.

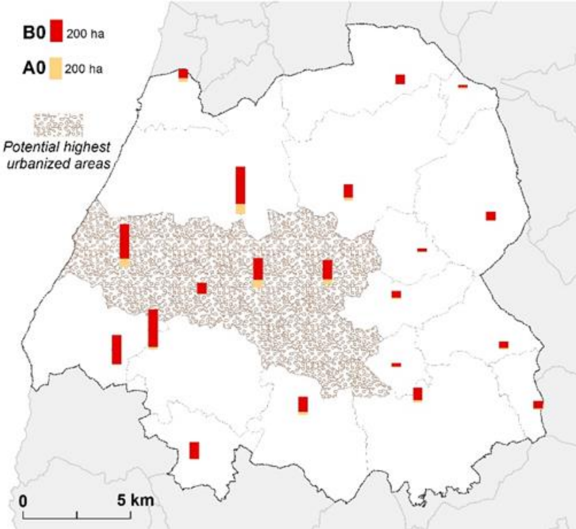

Figure 6.18 – Potential highest urbanizable areas and projected artificial surfaces in A0 (ANN-MLP) and B0 scenario (based on farmers' LUCC intentions plus ANN-MLP).

We verified high rates of artificial surfaces in B0 scenario in the parishes potentially most susceptible to further urbanisation (four in total). However, we also identified another three parishes with high rates of conversion, although these were not in the cluster of the highest potential to be converted into urban development. One such parish is located at the coast (A dos Cunhados), and other two in the southern (São Pedro da Cadeira e Ventosa) of the cluster of higher potential. These areas show higher levels of urban pressure and high demand for urban land.

In order to verify the agreement between the projected artificial surfaces verified in the B0 scenario 2025 and the area expected to be urbanised (defined in the Master Plan of Torres Vedras), the kappa value (Cohen, 1960) was estimated. The value achieved was 0.4205, corresponding to a moderate agreement (McHugh, 2012).

5. Modelling farmers' LUCC intentions with ABM

In the third and last LUCC model performed, we draw up a model based on ABM to evaluate multiple alternative future land uses to better recognise the LUCC and to better support spatial planning. According to this, we designed an ABM model to establish an experiment of multi-outcomes. The purpose of this ABM model was to project trajectories to "what-if" scenarios, involving some spatial elements, such as land use layer, land use regulations, some physical and demographic drivers (please see Table 4.5), and farmer's LUCC intentions (encoded in the model).

5.1 FARMER model: design and implementation

Agriculture land use management requires the capacity to incorporate a diversity of purposes and to integrate all the desires of stakeholders responsible for its management. They are mainly farmers driven by different goals. Some are driven by economic incentives, while others are interested in preserving the long-term ecological functions of agriculture. Also, decision-makers are often-times motivated by economic growth and environmental protection. There are a wide number of spatial optimisation techniques able to integrate many and occasionally disagreeing/ divergent purposes. One of the most recognised due to its ability to create feasible resolutions is the ABM. To study the dynamics of agriculture management, ABM offers a simulation approach in which computer agents characterise the decision making of individual units (Manson, 2005; Parker et al., 2003). ABM is suitable for simulating LUCC in which the agents can be explicitly encoded into a spatial model to assess how the different LUCC intentions lead to the emergence of new land-use patterns.

The purpose of this chapter was to address the optimisation-complexity of LUCC using the four scenarios presented previously.

ABM toolkits

ABM tools are divided into modelling environments; open libraries; and computer network (Parker et al., 2003). Many ABM software and toolkits have been developed for social science (Banos et al., 2017), such as geography, economy, sociology or anthropology. Currently, there are almost one hundred platforms based on ABM (Railsback et al., 2006). Following, we describe some of the widely used (Railsback et al., 2006):

1) Cormas - Common-pool Resources and Multi-Agent Systems - is specially designed to simulate interactions between agents, identifying and solving territorial land-use conflicts (Page et al., 2000);
2) GAMA - Gis and Agent-based Modelling Architecture - is developed for modelling spatially explicit dynamics (Taillandier et al., 2012);
3) MASON - Multiagent Simulation Toolkit - is designed to support a large number of agents based on a single machine, foraging algorithms, and evolutionary computation (is written in Java) (Luke, 2014);
4) Repast - The Recursive Porous Agent Simulation Toolkit - seeks to support the development of flexible models of living social agents, and integrate libraries for neural networks, genetic algorithms, and social network modelling (North et al., 2006);
5) SWARM - allows interactive access, presents a graphical representation, and an assignment of an independent schedule for each simulation (Iba, 2013);
6) ASCAPE - Agent-Landscape - is one of the earliest ABM tools and was developed by the Centre on Social and Economic Dynamics (CSED), Brookings Institution. ASCAPE support complex model designs and running on Java-enabled platforms;
7) OBEUS - Object-Based Environment for Urban Simulation - is based on Geographic Automata System (GAS) (Castle and Crooks, 2006);
8) Geo-Relationship - allows to make spatial relationships between geographic automata of the same or different types (Benenson and Torrens, 2004), and;
9) NetLogo - is an integrated modelling environment designed for agent-based modelling, and provides a high-level of automated simulation experiments (Berryman, 2008).

NetLogo is one of the most widely used ABM (Ghosh, 2015). It was designed by Wilensky (2004) and was developed at the Centre for Connected Learning and Computer-Based Modelling at North-western University. NetLogo provides a powerful programming language (Railsback et al., 2006), often used to model natural and social phenomena, and complex behaviours systems (Morgado et al., 2012). According to their advantages, we choose NetLogo (version 6.0) to develop our ABM model. We had the concern of using open-source software, and we designed it from a user-friendly perspective to be easier to interpret by the users. The costs of our ABM model maintenance and data used are low.

FARMER model: an overview

Our ABM was designated as FARMER model (FARmers intentions of changing land use in MEtropolitan Regions) and was based on agent-based modelling technology. FARMER model represents a planning decision-making model approach that incorporates a built-in model using spatial data. FARMER model allows to identify futures LUCC according to a set of spatial parameters such as convert or not forest and semi-natural areas into agricultural land; farming or not in areas with a specific slope; and limit the artificial surfaces growth from a specific distance of the existing artificial surfaces and road network (to see the programming code please see Appendix IV).

FARMER model allows visualising the results spatially and graphically. The land use outputs can be exported georeferenced in ASCII format and the statistics in .dbf format. In Figure 6.19 is represented the FARMER model flowchart.

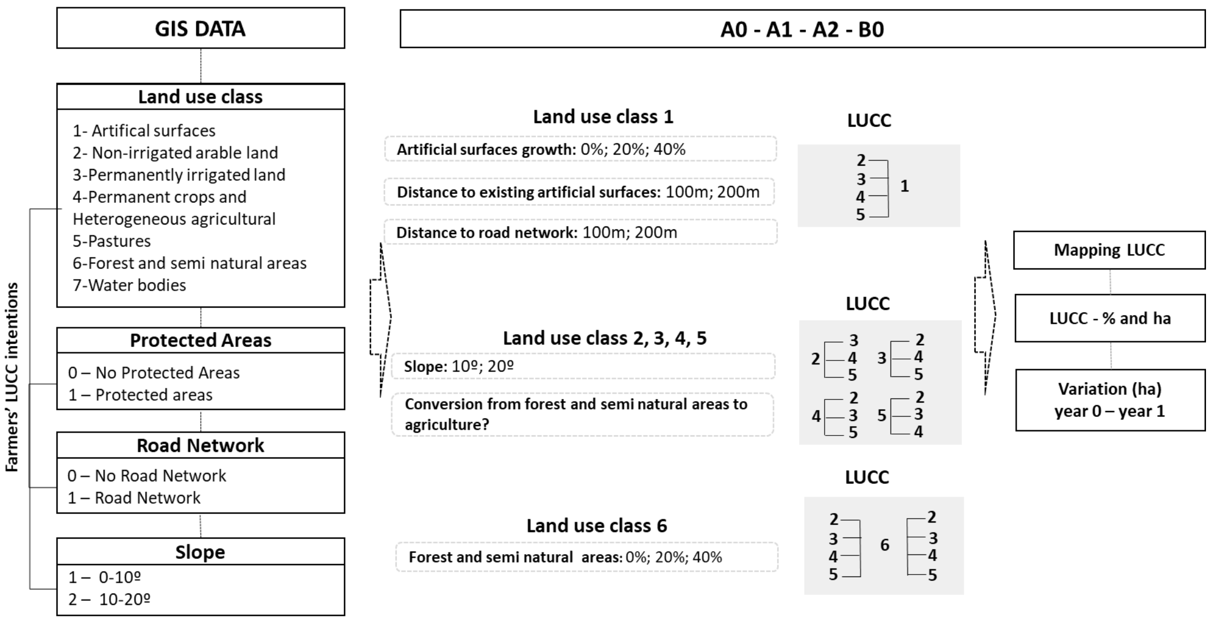

Figure 6.19 – FARMER model flowchart.

Spatial distribution

As stated previously, we considered seven heterogeneous land use classes: artificial surfaces, non-irrigated arable land, permanently irrigated land, permanent crops and heterogeneous agricultural land, pastures, forest and semi-natural areas and water bodies and wetlands. The spatial environmental also comprises protected areas, slope and road network. Each cell has the potential to be changed (with an exception for built-up areas, and water bodies and wetlands – these cells cannot be replaced). Farmers' LUCC intentions are distributed in each cell of non-irrigated arable land, permanently irrigated land, permanent crops and heterogeneous agricultural land, pastures, and forest and semi-natural areas.

Time, spatial resolution, and extends

The forecast horizon time is 2025. Each pixel represents an area of 1 hectare. This value was achieved according to the study dimension area, and the NetLogo characteristics and capabilities.

Design concept

FARMER model allows importing land use (time 0) in *ASCII format* (raster data). Simulation start in time $t = 0$ (land use 2010), and the projection period is 2025 ($t = 1$). Figure 6.20 shows the FARMER model interface.

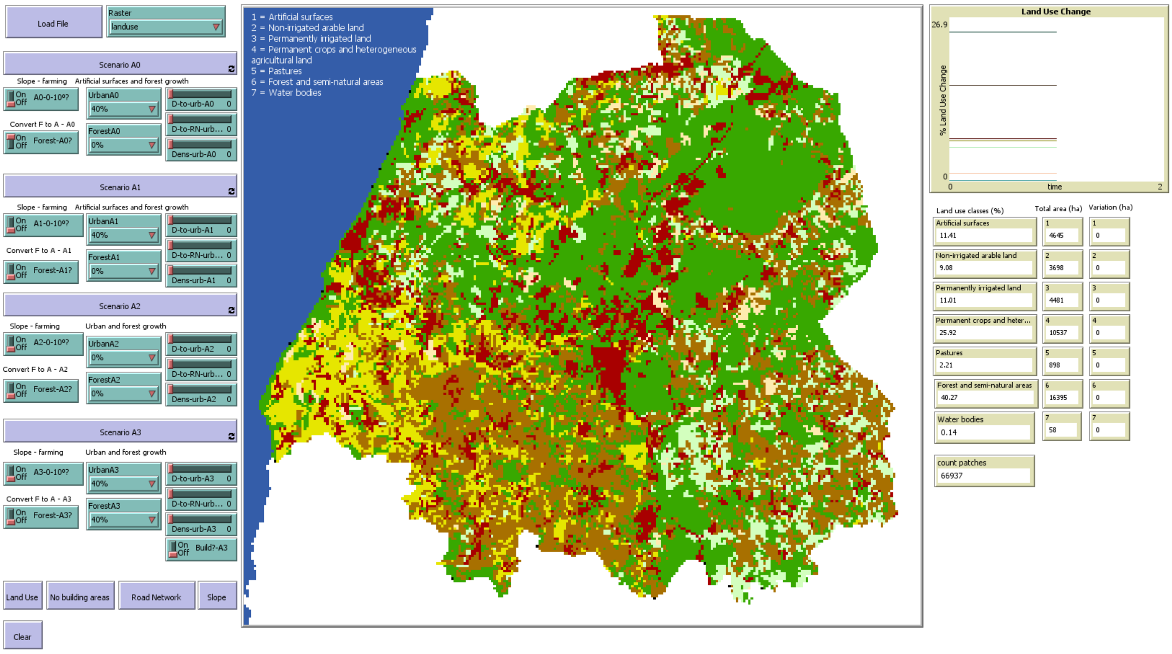

Figure 6.20 – FARMER model interface.

FARMER model: agents

Farmers identified their LUCC intentions according to the four studied scenarios. These intentions were estimated based on the change probability for each land-use class captured from the farmers' interviews (Table 6.11) (please see chapter 6, section 2).

Table 6.11 – Farmers' LUCC intentions – change probability (%) – by scenario and land-use class. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands.

Scenario	1	2	3	4	5	6	7
A0	0.00	0.06	20.00	10.00	-6.00	----	----
A1	0.00	3.00	68.00	71.00	-25.00	----	----
A2	0.00	-46.00	-17.00	-11.00	560.00	----	----
B0	47.80	0.28	-17.00	-1.00	-6.00	----	----

In each LUCC simulation is projected by a single time step. FARMER model has a quick response in each running simulation.

5.2 FARMER model: running simulations for A0, A1, A2, and B0 scenario

Many researchers have studied the importance to test the validity of ABM-LUCC models (An et al., 2005; Manson, 2005). Some of these tests represent a functional verification, which should be included efforts to break the model (Parker et al., 2003). These tests are used to control if the model is corrupted or produces entirely unreasonable results (An et al., 2005). The purpose is to identify the robustness of the model and recognises the inferences of any uncertainty assessment on simulation response (Helton, 2008), determining if there is a statistically significant change between simulation responses under different settings. To identify the perturbation and influence of each parameter on each simulation response, we used a function in NetLogo called *BehaviourSpace*, in which allows to perform a sweep for all potential simulations. We performed it using different settings, selecting a specific parameter in each of the following groups: artificial surfaces growth: 0%; 20%; or 40%; forest and semi-natural areas growth: 0%; 20%; or 40%; convert forest and semi-natural areas to agricultural land: Yes or No; farming 0-10º; farming 0-20º; distance to existence urban areas: 100m or 200m; and distance to road network: 100m or 200m. Following, we present a radar charter showing the LUCC in all potential simulations (Fig. 6.21).

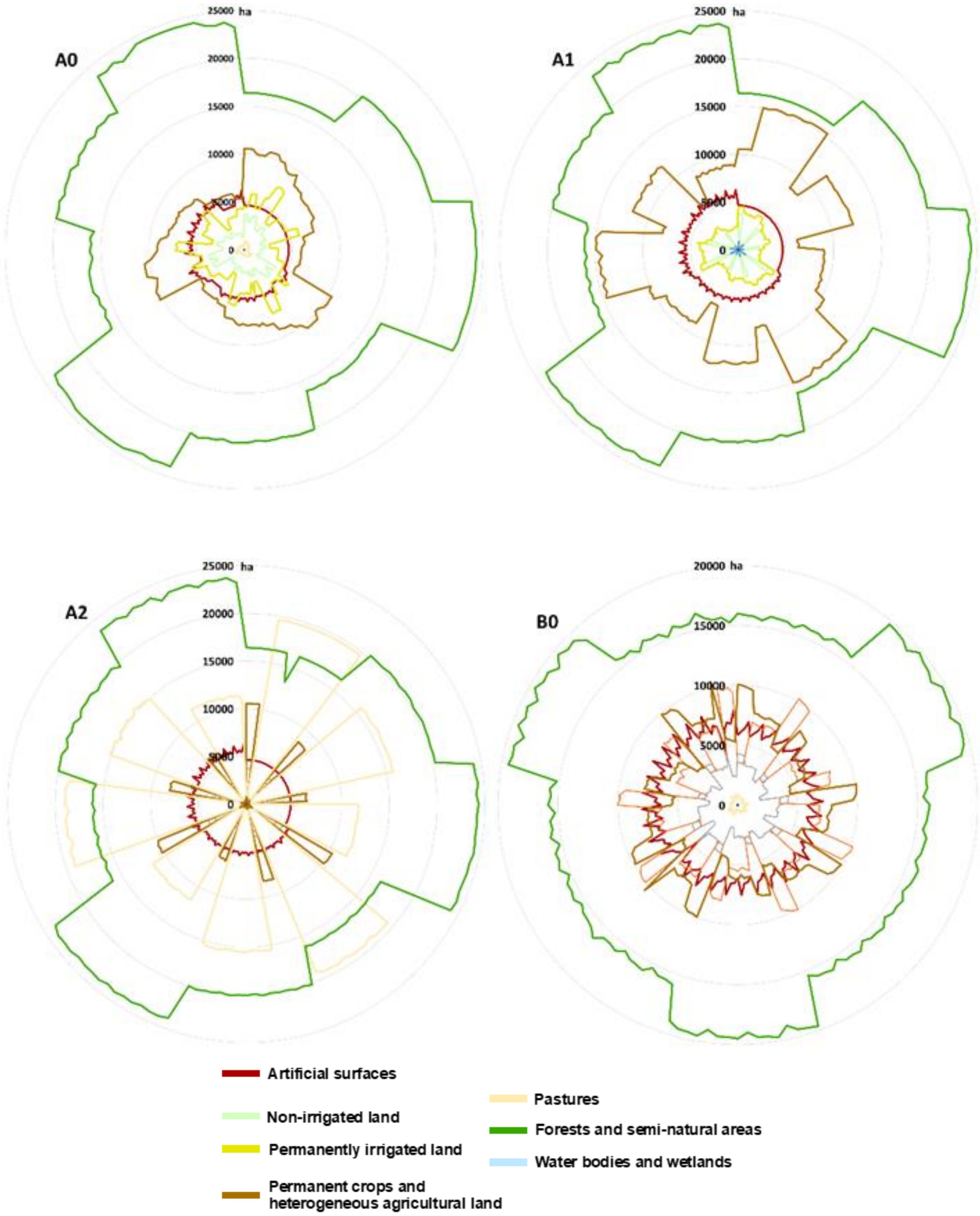

Figure 6.21 – FARMER model simulations (144 simulations).

Figure 6.21 represents the LUCC variation for each land-use class and for A0, A1, A2, and B0 scenario, according to the parameters mentioned above (to see the complete description of these radar charters, please see Appendix V).

Dissimilarities between A0, A1, A2, and B0 scenario

As demonstrated in Figure 6.21, different results in all possible 144 simulations for each scenario were verified. In the next chapter, we will identify the simulation (the one in the 144 possible simulations) that had the lowest deviations comparing to the stakeholders' LUCC visions (captured from a participatory workshop) for each scenario (in percentage).

Conclusion Chapter 6

As demonstrated in this chapter, LUCC is controlled by some indicators such as land use instruments, demographic, economic, and environmental drivers, topographic constraints, and human decisions.

The role of human activities in controlling land use has been noted to have different effects on land use. Anticipating LUCC decisions, indicating alternative futures and its consequences, to support policy-makers is one of the biggest challenges facing spatial planning. The analyses of how farmers play in the decision-making process (local-level actors) and their interactions between other factors and constraints allow verifying how, where, why and what land-use conversions may occur. In this chapter, we introduced advances in land use modelling, complex dynamics, and planning purposes, using CA-Markov, ANN-MLP, and ABM models based on farmers' future LUCC intentions. We identified suitable land uses to avoid futures consequences.

These models were performed to identify LUCC in the following scenarios: A0 - BAU; A1 – regional food security; A2 - climate change; and B0 - farming under urban pressure. These models presented in this chapter were capable of measuring the implications for land use and environment, and as the final goal to be integrated into planning processes. These models allow anticipating plausible futures to better understand the space-time land-use dynamics, providing guidance and strategies that can be applied in spatial planning and management of land.

In the next chapter, a discussion regarding the achieved results in this research, and an approach to engaging stakeholders into the LUCC models outcomes will be performed.

Chapter 7 – LUCC models discussion: stakeholders' engagement

Introduction Chapter 7

Chapter seven is the last chapter of this PhD thesis. In this chapter, we discussed the relevance to better understand LUCC over time, and we debated the strengths and weakness of each LUCC model performed. In addition, we presented the results of a participatory workshop with local stakeholders held in Torres Vedras. This workshop had as the main goal to engage stakeholders in the LUCC models discussion and validation process. We also debated the importance of using mixed methods in the decision-making process.

1. LUCC models: understand the past and the present to think about the future

There is a real need to understand the LUCC in the past and the present, recognise its causes, and simulate LUCC into the future to monitor its dynamics. The analysis of future LUCC can inform decision-makers, preventing land degradation, and allowing a better understanding of the mechanisms for different responses. A set of techniques can be used to analyse agricultural land-use changes, spatially and temporally, allowing to monitor, and to create measures to avoid land-use classes of being fragmented, thus promoting the existence of agricultural land areas of higher dimension.

LUCC models can provide optimum assistance to end-users (Liu et al., 2016; Xiaoli et al., 2009). In the previous chapter, we presented three different models to conduct simulations and modelling LUCC in Torres Vedras municipality. They attend to understand what-if questions and evaluate alternative futures (Epstein, 1999). Time can be fast-tracked and can support critical issues with an interactive, and visual approach (Torrens, 2006) to understand the unpredicted consequences of farmers' actions. The evolution between static into dynamic models was not a one-step procedure. Static models, e.g., Alonso (1960), initially yielded place to recursive models, e.g., Maddala and Lee (1976) before being converted into dynamic models (Beaumont, 1981; Wegener, 1985). Effective developments in the LUCC dynamic models occurred only by the 1980s, when CA and ANN models started to be applied, e.g., Couclelis (1985), Deadman (1993), Batty and Xie (1997), Portugali (2000), and White and Engelen (2000). Nonetheless, ABM emerging during the mid-1990s (Forrest and Jones, 1995).

There is an increasing amount of research about using these LUCC models, e.g., Parker (2002), Pontius (2004), and Veldkamp and Lambin (2001). They are critical for understanding land-use dynamics and supporting land-use planning and decision making. One of the major challenges in its implementation is to couple human behaviours and environmental, demographic and economic driving forces. In this research, we attempt to incorporate all these features in the LUCC models performed. Below in Table 7.1 strengths and weaknesses are described, for each LUCC model examined.

Table 7.1 – LUCC models: strengths and weaknesses.

Method	Strengths	Weaknesses
CA-Markov chain	- transition probability maps based on farmers' LUCC intentions were created; - outputs in the more accurate quantity of change value; and - the probability of each cell is estimated.	- cells allocation start from the nearest cells to the changed cells; and - in some areas, the available data is not enough to estimate good transition probabilities.
ANN-MLP	**ANN-MLP** – ***Artificial surfaces allocation*** - it allows to integrate artificial surfaces allocation in the model, based on a business-as-usual scenario (identifying potential areas that can be converted into urban development); and - it does not require a complex algorithm to build an accurate model. **Farmers' interviews –** ***Agricultural land allocation*** - it allows identifying precise quantification of farmers' LUCC intentions by directly relate these intentions with the same proportion of land use classes.	**ANN-MLP** – ***Artificial surfaces allocation*** - only artificial surfaces were considered; - nonlinear relationships; and - it requires high processing time; **Farmers' interviews –** ***Agricultural land allocation*** - It is limited to questions and scenarios we have done in this research; and - random allocation of LUCC was defined (while land restrictions were considered).
ABM	- flexibility: a diversity of rules can be integrated into the model, e.g., farmers' LUCC intentions; land restrictions; and potential areas to be converted; and - low cost and time-saving approach.	- multi-simulations can be viewed as strengths and weaknesses. However, as a weakness multi-simulation creates uncertainties about identifying the best final map for each scenario; and - difficulty to verify models' validity and check its accuracy level.

As is underlined the greatest advantage of performing CA-Markov-LUCC model was to integrate transition probability matrices based on farmers' LUCC intentions and transition probability maps based on driving forces. CA-Markov-LUCC also has the aptitude to simulate dynamic developments from a bottom-up perspective (Liu et al., 2008a). Regarding ANN-MLP-LUCC model (in projecting artificial surface growth) has as the main goal to reproduce the human brain (using a machine learning) without previous knowledge of its functional form (Zou et al., 2009), identifying complex behaviours and patterns. And the greatest advantage of using ABM-LUCC model was its flexibility, namely the use of a multiplicity of rules that could be integrated into the model, and the interaction of agents that have the capability to make decisions (Macal and North, 2009).

As demonstrated each model has its specific strengths and weaknesses, and we cannot say that there is one better LUCC model than other. However, in an attempt to identify which model, according to the outcomes of each scenario, is more adapted to the characteristics of the territory, we organised a participatory workshop, engaging representative stakeholders of

Torres Vedras (the LUCC models outcomes considered for this analysis were the CA-Markov chain and ANN-MLP – we did not consider the ABM-LUCC model due to its multi-outcomes for each scenario). Stakeholders could identify, according to their visions, the LUCC model that they consider better adjusted in each scenario. Stakeholders' engagement allowed to identify their interests, increasing the complexity of the LUCC models performed, and allowed to decrease the uncertainties of the outcomes. We believe that this approach is one step towards understanding the implications of LUCC in the future.

2. Participatory workshop for LUCC models validation and land use planning decision-making

This section introduces to the topic of how a participatory workshop can be suitable to analyse and validate the achieved results. We presented a step-by-step methodology to explain how this workshop was applied in our case study engaging local stakeholders. This workshop aimed to evaluate the efficiency of the LUCC models and to identify the LUCC model better adjusted in each scenario towards better land-use planning.

2.1 Participatory workshop: stakeholders' engagement

The participatory workshop provided one step forward to integrate stakeholders' LUCC visions and to identify better land use and management practices. Combine multiple stakeholders' visions allowed to verify the complexity of decisions that land planners must have to improve land-use strategies.

A participatory workshop in Torres Vedras engaging local stakeholders was performed. In this workshop, we captured the LUCC visions from each stakeholder to the four studied scenarios. Based on this purpose, we engaged seven participants that comprise a wide range of interests. We invited representative stakeholders (by phone and e-mail) (that fit their responsibilities in Torres Vedras municipality) of the following main areas of land management: i) land use planning; ii) real estate developer; iii) agriculture; and iv) forest. We had positive responses from all land-use groups, with exception from the real estate developer group. In this sense, the participants of the participatory workshop were:

a) land use planning: 1 planning technician from Torres Vedras city council;

b) agriculture: 1 element from Farmers Association of Torres Vedras; 1 element from LEADEROESTE - Rural Development Association; 1 element from Confederation of Farmers of Portugal (CAP-OESTE); and 1 farmer (selected randomly from the sample of the interviewed farmers);

c) forest land-use group: 1 element from AFLOESTE association; and 1 element from APAS Forest association.

The participatory workshop was performed using a round-table to allow stakeholders to communicate and think spatially. The selected stakeholders, with their roles of great importance for the interpretation and analysis of the outcomes in this research, comprises those parties who are affected by land use management decisions, those who can determine such decisions, as well as those who intend to determine LUCC. As a central and final purpose to include stakeholders together was to analyse and validate LUCC models' outcomes.

It was proposed that the workshop consists of three hours of meeting, bringing together the mentioned participants. The workshop was conducted on January 29rd, 2019 (from 10 a.m. until 1 p.m.) at Centro de Educação Ambiental (Environmental Education Centre) in Torres Vedras (Fig. 7.1). All participants were informed about the content of this study and gave their informed consent to publish their responses (however, they are mentioned anonymously).

Figure 7.1 – Participatory workshop at Centro de Educação Ambiental (Environmental Education Centre) in Torres Vedras.

The workshop started with a thirty-minute presentation showing the main results achieved in this PhD research, followed by 2h30 of analysis and discussion regarding the LUCC models results (Portuguese was the language spoken in the workshop). It allowed exchanging knowledge from different points of view, to discuss individual visions concerning the LUCC, to recognise lacks, as well as to express recommendations.

The LUCC models allowed the conception of a reliable picture of future land use, quantification and through its results point out territorial dynamics and trends. The use of different models to simulate the same phenomena, in the same studied area, helped to minimise the uncertainty associated with the achieved results.

LUCC models outcomes (CA-Markov and ANN-MLP) were showed to the stakeholders. Figure 7.2 shows the methodology flowchart of both LUCC models (to see the complete results and methodology adopted in each model, please see chapter 6).

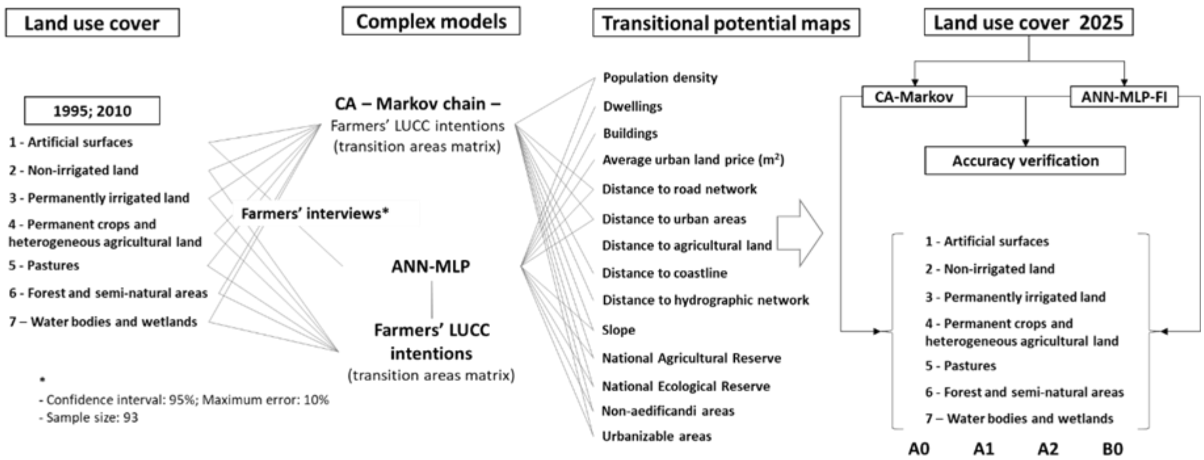

Figure 7.2 – LUCC models (CA-Markov and ANN-MLP): methodology flowchart.

The results in percentage, as well as the printed maps of each LUCC model and scenario (printed at A3 format), were used as the basis for this participatory workshop (Fig. 7.3 and Table 7.2).

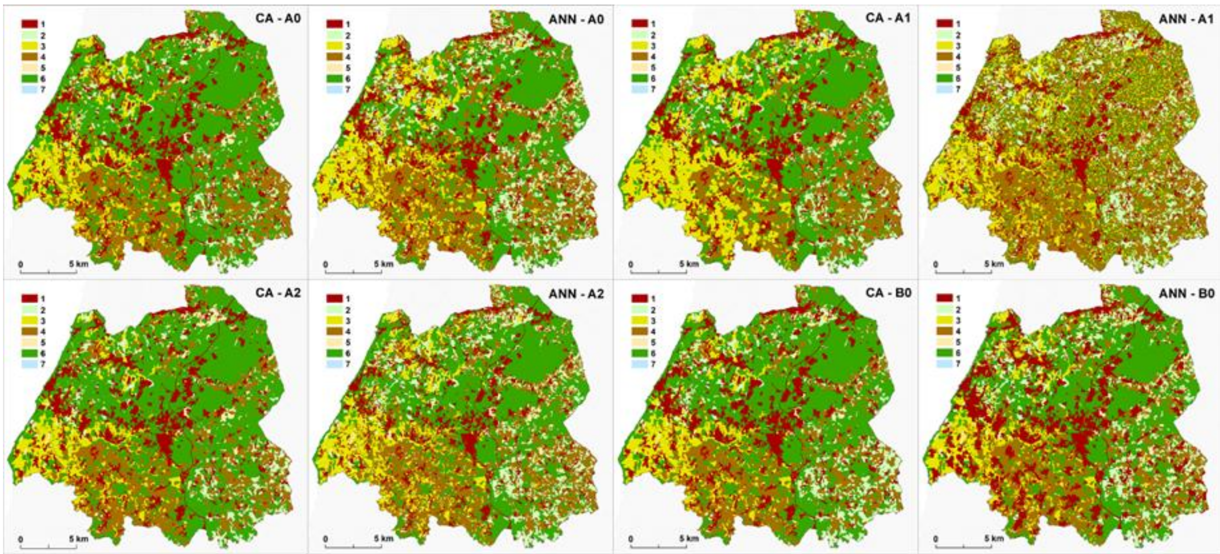

Figure 7.3 – LUCC maps: CA-Markov and ANN-MLP - A0, A1, A2 and B0 scenario.

Table 7.2 – LUCC (%): CA-Markov and ANN-MLP - A0, A1, A2 and B0 scenario. Land use classes: 1 - artificial surfaces; 2 - non-irrigated land; 3 - permanently irrigated land; 4 - permanent crops and heterogeneous agricultural land; 5 - pastures; 6 - forest and semi-natural areas; and 7 - water bodies and wetlands.

LUC	2010	A0 – CA (%)	A0 – ANN (%)	A1 – CA (%)	A1 – ANN (%)	A2 – CA (%)	A2 – ANN (%)	B0 – CA (%)	B0 – ANN (%)
1	11.40	14.77	12.71	14.41	11.36	14.77	11.40	16.11	17.13
2	9.09	5.16	9.57	6.44	9.32	5.31	8.76	8.11	9.25
3	11.00	10.48	13.30	18.47	18.41	8.34	10.68	9.22	8.80
4	25.94	21.73	28.59	21.78	44.29	20.72	25.21	20.29	23.85
5	2.17	1.44	2.14	0.87	2.16	1.94	3.55	1.16	2.07
6	40.25	46.27	33.55	37.87	14.30	48.75	40.25	44.96	38.75
7	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Accompanied by the printed maps one questionnaire was distributed to each participant. The questionnaire had four main parts. The first part was related to LUCC models analyses, the second regarding the LUCC models evaluation, the third concerning the LUCC models as a support decision system, and the fourth part about the workshop evaluation (Table 7.3).

Table 7.3 – Questionnaire addressed to stakeholders. 1. LUCC models analysis; 2. LUCC models evaluation; 3. support decision system; and 4. workshop evaluation.

Part	Questions
1	a. Which LUCC model (CA-Markov or ANN-MLP) do you consider that have better results?
	b. According to the chosen LUCC model, do you consider the location of the LUCC plausible?
	c. According to the chosen LUCC model, do you consider that the % values for each LUC meet your vision? (if not, please indicate the values in %).
2	a. Are the LUCC models clear and easy to follow? 1 (lowest score) - 5 (highest score)
	b. Are the data presented satisfactory to raise awareness regarding LUCC? 1 (lowest score) - 5 (highest score)
	c. Any suggestion?
3	a. Do you think that LUCC models are informative and useful to support land use planning? 1 (lowest score) - 5 (highest score)
	b. Do you think that LUCC models are valuable to raise awareness concerning the LUCC impacts? 1 (lowest score) - 5 (highest score)
	c. Would you recommend this LUCC analysis to other case studies (other municipalities)? 1 (lowest score) - 5 (highest score)
4	a. How do you rate the relevance of this participatory workshop in the collaborative participation? 1 (lowest score) - 5 (highest score)
	b. How do you rate the organisation of this participatory workshop, and how this participatory workshop took place? 1 (lowest score) - 5 (highest score)
	c. Any suggestion?

In the sections below, we will show the results obtained in this questionnaire, the main conclusions derived from the discussion performed at the end of the workshop, as well as how we integrated the stakeholders' LUCC visions into the FARMER model. Although seven participants were present in the workshop, one of them (from the agriculture land use group) not filled out the questionnaire accompanied by the interpretation of the maps, because this participant felt difficulty in its interpretation. However, this participant actively collaborated in the theoretical discussion of the results.

2.2 LUCC models analysis and validation

In the first part of the questionnaire, stakeholders identified the best suited LUCC model according to their expectation for each scenario (they chose between the CA-Markov and ANN-MLP model). Then, we asked them if they considered the location of the LUCC plausible. And finally, even if they had chosen one model, and even if they had considered the location plausible, but if they did not agree about the percentage of each land-use class, they had the hypothesis to indicate what values were according to their expectation.

Therefore, according to the results, five in six participants chose CA-Markov as the best-fitted LUCC model in the A0 scenario; also, five in six considered plausible the LUCC location; and two in six did not agree about the % of each LUCC. Table 7.4 shows the percentage of each land-use class according to the stakeholders' visions in the A0 scenario.

Table 7.4 – A0 scenario: stakeholders' LUCC visions. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

Stakeholder	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
1	12.71	9.57	13.3	28.59	2.14	33.54	0.15
2	14.77	7.16	12.48	23.73	1.44	40.27	0.15
3	14.77	5.16	14.48	21.73	1.44	42.27	0.15
4	14.77	3.00	20.00	20.00	10.00	29.23	3.00
5	14.00	6.85	11.00	26.00	2.00	40.00	0.15
6	14.77	5.16	10.48	21.73	1.44	46.27	0.15

In A1 scenario, all stakeholders elected CA-Markov LUCC model as the best-suited model taking into account their visions. Only one participant in six did not agree about the location of LUCC. However, all of them agreed about the total percentage of LUCC. According to these results, stakeholders' LUCC visions were the same for all land use classes and were based on the LUCC results of CA-Markov model (Table 7.5).

Table 7.5 – A1 scenario: stakeholders' LUCC visions. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

Stakeholder	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
1	14.41	6.44	18.47	21.78	0.87	37.88	0.15
2	14.41	6.44	18.47	21.78	0.87	37.88	0.15
3	14.41	6.44	18.47	21.78	0.87	37.88	0.15
4	14.41	6.44	18.47	21.78	0.87	37.88	0.15
5	14.41	6.44	18.47	21.78	0.87	37.88	0.15
6	14.41	6.44	18.47	21.78	0.87	37.88	0.15

In A2 scenario four in six stakeholders selected the CA-Markov LUCC model as the best-suited model. Five in six participants agreed with the LUCC location. And only two (in six) did not agree about the percentage of LUCC. Table 7.6 displays in detail the percentage of each stakeholders' LUCC visions for the A2 scenario.

Table 7.6 – A2 scenario: stakeholders' LUCC visions. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

Stakeholder	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
1	11.40	9.76	11.68	25.21	4.55	37.25	0.15
2	14.77	5.31	8.34	20.72	1.96	48.75	0.15
3	14.77	5.31	8.34	20.72	1.96	48.75	0.15
4	14.77	3.00	23.23	20.00	10.00	26.00	3.00
5	14.77	5.31	8.34	20.72	1.96	48.75	0.15
6	11.40	8.76	10.68	25.21	3.55	40.25	0.15

Finally, in B0 scenario, three stakeholders identified the ANN-MLP LUCC model, and the other three selected CA-Markov LUCC model as the best-suited models according to their visions. Five in six stakeholders agreed with the LUCC location, and only one did not agree about the percentage of each land-use class according to the chosen model. The final percentage achieved by the stakeholders for the B0 scenario is expressed in Table 7.7.

Table 7.7 – B0 scenario: stakeholders' LUCC visions. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

Stakeholder	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
1	16.11	8.11	9.22	20.29	1.16	44.96	0.15
2	16.11	8.11	9.22	20.29	1.16	44.96	0.15
3	16.11	8.11	9.22	20.29	1.16	44.96	0.15
4	25.00	3.00	18.00	15.00	10.00	26.00	3.00
5	17.13	9.25	8.80	23.85	2.07	38.75	0.15
6	17.13	9.25	8.80	23.85	2.07	38.75	0.15

As demonstrated CA-Markov was the most elected LUCC model by stakeholders for A0, A1, and A2 scenario. This was verified, probably due to the fact of the CA-Markov model be based on the neighbourhood principle (please see chapter 3, section 3.2). The expansion of the land use classes is verified by contiguity and this can reflect the idea of what stakeholders think regarding the LUCC for these three different scenarios. Nevertheless, in the case of B0 scenario, the choice was not consensual. Three stakeholders mentioned the CA-Markov as the more adjusted model, and the other three stakeholders considered the ANN-MLP LUCC model as the more adjusted according to their expectations. As previously mentioned, ANN-MLP is based on the principle of spatial expansion distribution as a complex behaviour and not necessarily by spatial contiguity (please see chapter 3, section 3.3), and perhaps, for this reason, these stakeholders considered that this can represent a more realistic situation concerning the growth of the artificial surface in B0 scenario.

In the second, third, and fourth part of the questionnaire, we asked the stakeholders about the reliability of the LUCC models, the relevance of these models as a support for decision-making, as well as evaluation about the way of how this participatory workshop was organised.

According to the answers, based on a scale ranging between 1 (lowest score) and 5 (highest score), the mean of the responses for the ease of LUCC maps interpretation was 4 (value considered as very good). The same value was obtained in the answer about if they find the results satisfactory for raising awareness in the LUCC analysis. They considered a relevant approach in the deliberative decision-making process, as well as a way of recognising the importance of the perception of others to achieve a shared solution.

As suggestions to improve the reliability of the LUCC models, stakeholders have pointed out to include less land use classes; to show the urban perimeters, and to show the names of the localities on the map to improve the readability; as well as to separate the land use class forest and semi-natural areas into three other land use classes, such as forest, bush areas, and uncultivated areas.

Moreover, in the part of the questionnaire about decision support, stakeholders classified as very good - 4 (mean value - scale from 1 to 5), the possibility of these LUCC models being informative and as a support in land use planning. Regarding the question about if they recommend this analysis to other cases studies the answer was of high recommendation (the mean value obtained was 4). They suggested developing similar approaches to other municipalities, indicating that these LUCC models can be effectively used as a support for participatory spatial planning and applied into municipal planning policies and regulations.

These recommendations aided to set limits to the models' complexity as well as to determine its lacks.

In the last part of the questionnaire, stakeholders were asked to provide an evaluation of the efficacy and usability of the workshop, identifying positive and negative aspects, and mentioning why. In the evaluation of the relevance of this participatory workshop, they considered very importantly (the mean value was 4), and they found very good (4 – scale 1-5) the way the organisation of this workshop took place.

2.3 Participatory workshop: integrating stakeholders' LUCC visions into FARMER model

In this section, we presented an experimental exercise, based on the stakeholders' LUCC visions for each scenario. We identified through the FARMER model the parameters needed to achieve similar results in terms of percentage for each land-use class (Figure 7.4). This exercise allowed to reduce one of the weaknesses presented by the ABM-LUCC model: the multi-outcomes. Thus, by choosing the simulation that presents the lowest deviations comparing with the stakeholders' LUCC visions, we reduced the uncertainties, by increasing the accuracy level of outcomes.

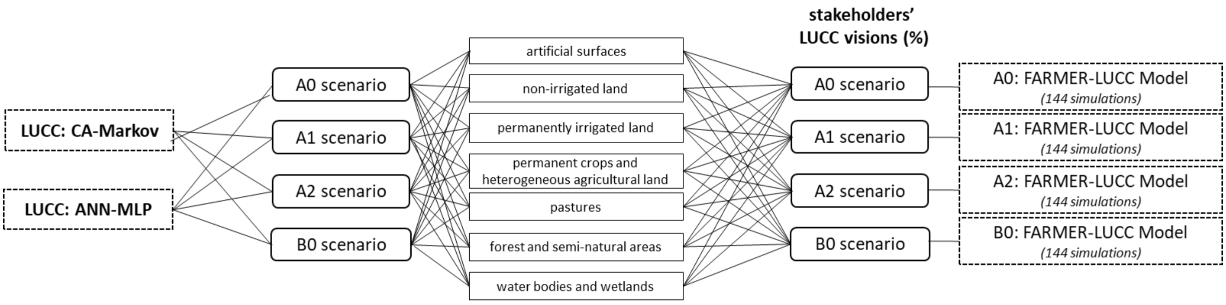

Figure 7.4 – Integrating stakeholders' LUCC visions into FARMER model.

The first step was to find the stakeholders' LUCC visions for each scenario (global vision). Thus, we find the value for each scenario and for each land-use class (Table 7.8).

Table 7.8 – Stakeholders' LUCC visions – A0, A1, A2, and B0 scenario. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

LUCC visions (global vision)	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
A0	14.30	6.15	13.62	23.63	3.08	38.60	0.63
A1	14.41	6.44	18.47	21.78	0.87	37.88	0.15
A2	13.65	6.24	11.77	22.10	4.00	41.63	0.63
B0	17.93	7.64	10.54	20.60	2.94	39.73	0.63

The second step was to find in all possible 144 simulations (for each scenario) in the FARMER model, the simulation that had the lowest deviation in comparison to stakeholders' LUCC visions (Table 7.9).

Table 7.9 – Stakeholders' LUCC visions and selected simulation in FARMER model for A0, A1, A2, and B0 scenario. Land use classes: 1 – artificial surfaces; 2 – non-irrigated arable land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas; 7 – water bodies and wetlands.

Land use classes	1	2	3	4	5	6	7
Initial state	11.41	9.08	11.01	25.92	2.21	40.27	0.14
Scenario	**A0**						
Stakeholders' LUCC visions (%)	14.30	6.15	13.62	23.63	3.08	38.60	0.63
Selected simulation A0 (%) – FARMER model	13.96	7.12	14.14	23.45	1.76	39.43	0.14
Deviations	0.34	-0.97	-0.52	0.18	1.32	-0.83	0.49
Scenario	**A1**						
Stakeholders' LUCC visions (%)	14.41	6.44	18.47	21.78	0.87	37.88	0.15
Selected simulation A1 (%) – FARMER model	15.34	8.68	10.39	24.37	2.10	38.98	0.14
Deviations	-0.93	-2.24	8.08	-2.59	-1.23	-1.1	0.01
Scenario	**A2**						
Stakeholders' LUCC visions (%)	13.65	6.24	11.77	22.10	4	41.63	0.63
Selected simulation A2 (%) – FARMER model	13.31	8.87	10.74	25.09	2.17	39.68	0.14
Deviations	0.34	-2.63	1.03	-2.99	1.83	1.95	0.49
Scenario	**B0**						
Stakeholders' LUCC visions (%)	17.93	7.64	10.54	20.60	2.94	39.73	0.63
Selected simulation B0 (%) – FARMER model	18.41	8.30	10.01	23.22	2.05	37.87	0.14
Deviations	-0.48	-0.66	0.53	-2.62	0.89	1.86	0.49

Therefore, we identified the parameters needed to achieve those outcomes. The possible parameters are: artificial surfaces growth: 0%; 20%; and 40%; distance to artificial surfaces (100m and 200m); distance to road network (100m and 200m) (non-aedificandi areas are incorporated in the model by default); farming 0-10º; farming 0-20º; forest and semi-natural areas growth: 0%; 20%; and 40%; convert forest to agriculture; do not convert forest to agriculture. In addition, a probability of change for each land-use class and scenario (in %) based on the farmers' LUCC intentions is incorporated by default in the FARMER model. Table 7.10 shows the parameters needed to achieve the selected simulation in each scenario displayed in Table 7.9.

Table 7.10 – FARMER model parameters. Group: a – artificial surfaces; b – agricultural land; c – forest and semi-natural areas; d – water bodies and wetlands.

Group		A0	A1	A2	B0
		Farmers' LUCC intentions (%) - static			
a	1 - Artificial surfaces (%)	0.00	0.00	0.00	47.80
		plus			
		Parameters (%)			
		40.00	40.00	40.00	20.00
	Distance to artificial surfaces (m)	100	200	200	200
	Distance to road network (m)	200	200	100	200
		Farmers' LUCC intentions (%) - static			
b	2 - Non-irrigated arable land	0.06	2.90	-45.61	0.28
	3 - Permanently irrigated land	20.23	67.97	-17.06	-17.00
	4 - Permanent crops and heterogeneous agricultural land	10.03	71.32	-11.00	-1.00
	5 - Pastures	-6.35	-25.40	560.32	-6.00
		plus			
		Parameters (%)			
	Farming (slope in º)	0-10	0-20	0-20	0-20
	Convert forest and semi-natural areas to agricultural land use classes?	Yes	Yes	Yes	Yes
		Farmers' LUCC intentions (%) - static			
c	6 - Forest and semi-natural areas	0.00	0.00	0.00	0.00
		plus			
		Parameters (%)			
		0.00	0.00	0.00	0.00
		Farmers' LUCC intentions (%) - static			
d	7 - Water bodies and wetlands	0.00	0.00	0.00	0.00

As we can verify in Figure 7.10, farmers' LUCC intentions (%) are the most determinant parameter responsible for the LUCC in the selected simulation for each scenario, as well as distance to artificial surfaces, distance to road network, and farming slope parameter.

At the end of the workshop, stakeholders were asked: which LUCC they think, according their own visions, will be verified in 2025? After an acutely discussion they reached a LUCC consensus which is expressed as follows: artificial surfaces 16%; non-irrigated land 4.5%; permanently irrigated land 16%; permanent crops and heterogeneous agricultural land 27.94%; pastures 2%; forest and semi-natural areas 31.56%; and water bodies and wetlands 2%.

Therefore, in order to hierarchize the most plausible scenarios according to these values, we estimated the deviations between these values and the values of the global stakeholders' LUCC visions for each scenario (Table 7.11). Following this order, the most plausible scenario is A0, followed by A1, A2, and by B0 scenario.

Table 7.11 – Stakeholders' LUCC visions (%) for 2025. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7	Total
LUCC visions (2025)	**16.00**	**4.50**	**16.00**	**27.94**	**2.00**	**31.56**	**2.00**	
Deviations								
(global vision) A0	1.70	-1.65	2.38	4.31	-1.08	-7.04	1.37	19.53
(global vision) A1	1.59	-1.94	-2.47	6.16	1.13	-6.32	1.85	21.46
(global vision) A2	2.35	-1.74	4.23	5.84	-2.00	-10.07	1.37	27.60
(global vision) B0	-1.93	-3.14	5.46	7.34	-0.94	-8.17	1.37	28.35

Consequently, we spatialized this simulation, that expresses the consensual LUCC transformation which stakeholders think, according to their knowledge, will be verified in 2025 (Fig. 7.5).

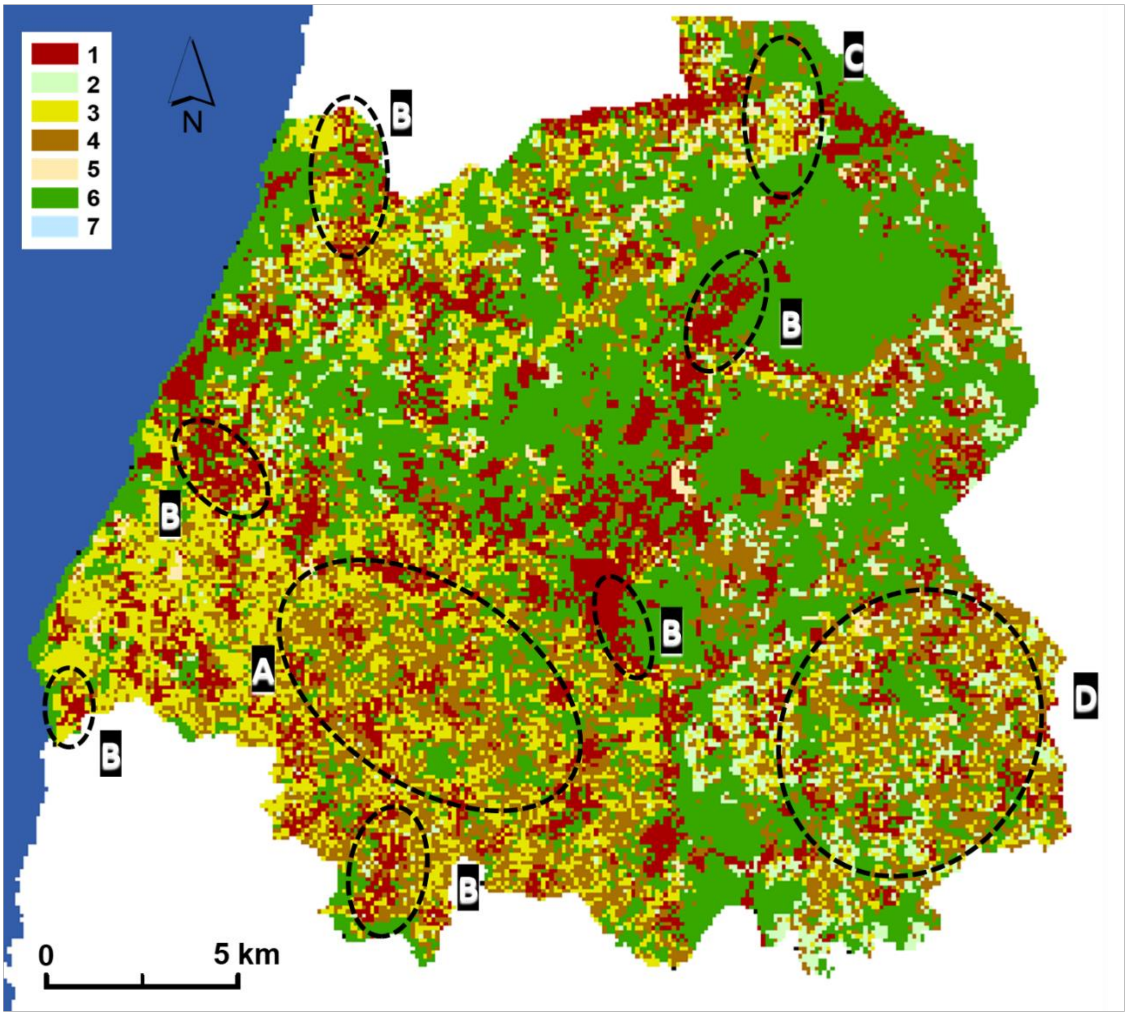

Figure 7.5 – Land use cover 2025: stakeholders' LUCC vision (A0: selected simulation – Stakeholders-LUCC model). Land use classes: 1 – artificial surfaces; 2 – non-irrigated arable land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas; 7 – water bodies and wetlands.

Figure 7.5 allows verify spatially these transformations. In the location assigned by A, we identify the site where the probability of conversion from permanent crops and heterogeneous agricultural land to permanently irrigated land is higher. In the location assigned by B which represents the artificial surfaces' growth, we recognized that artificial surfaces expansion occurs along the road network, and mainly infilling around existing artificial surfaces. The spatial patterns of this artificial surface' growth are categorized by linear directions, more marked in the south and west directions.

Moreover, the location C marks one of the highest transitions from non-irrigated arable land to permanently irrigated land, and location D from permanent crops and heterogeneous agricultural land and non-irrigated arable land to permanently irrigated land. The loss of forest and semi-natural areas is verified throughout the municipality, especially near their limits, consumed by artificial surfaces and agricultural land.

As demonstrated above the participation of the representative stakeholders was critical to successfully examine and validate and analyse the LUCC models presented in this research.

In the next section, we will mention the importance of using these mixed methods in the decision-making process.

3. Importance of mixed methods in the decision-making process

Engaging stakeholders in the decision-making process (Hersperger et al., 2010; Schreinemachers and Berger, 2006), have been identified as a useful tool for exploring changes in ecological systems (Brady et al., 2012; Rounsevell et al., 2005), and an essential step for better spatial planning.

Preserving agricultural areas has become critical for policy-makers, who seeking to protect food security and to maintain farming as a livelihood. In many countries, policy instruments in place have not been useful tools for keeping agricultural practice (Abrantes et al., 2016; Martellozzo et al., 2018). Tobe effective, spatial planning policies involving local decision-making and public participation could (1) comprise agricultural security areas (Larson et al., 2001); (2) promote links between farmers and consumers (Lea et al., 2006); and (3) create urban containment policies (Gomes et al., 2018). The change detection analysis aid generates up-to-date information to support planning and decision making (Puertas et al., 2014).

In this PhD research different LUCC modelling approaches, recognising farmers' LUCC intentions were analysed, compared, discussed, and validated. The engagement of farmers and stakeholders in this study allowed to improve the knowledge of LUCC dynamics in Torres Vedras and to reduce future uncertainties, as well as allowed raise awareness by involving them in the building of the LUCC models (by farmers), and in the LUCC models validation and examination (by stakeholders). Using multi-methods, incorporating insights from different actors demonstrated how the outcomes could most effectively support decision-makers. These methods can provide a better LUCC understanding, allowing to develop new hypotheses that can support spatial planning.

The participatory workshop allowed to improve decision-makers perception about the importance of a spatial and temporal LUCC analysis. Combine multiple stakeholders' perspectives allowed to integrate their objectives towards policy and decision-making, providing one step forward to create better land use and management practices. According to this analysis, decision-makers can become more aware of future LUCC, and stakeholders more conscious about the complex trade-off decisions that land planners must identify to improve land-use strategies. Stakeholders interaction might seem like a source of land use conflict due perhaps they might have divergent opinions. However, methods such as weight their opinions in the negotiation process should be a good solution to help decision-makers towards better land-use strategies.

Conclusion Chapter 7

This chapter illustrated how LUCC analysis could be evaluated numerically and qualitatively integrating stakeholders' knowledge. Although the emerging of LUCC models and their coupling with GIS, a gap between decision-makers and science still persist. However, in this chapter, we introduced some methods and techniques to minimise this gap. Stakeholders' feedback has demonstrated to be appropriate to reach consensus, reinforcing the relevance of integrating complexity analysis to address land-use planning questions.

These results can support local and regional stakeholders in LUCC decision-making processes indicating alternative futures and showing how, where, and which land-use conversions may occur. According to the results obtained, we identified suitable land uses to avoid undesirable future consequences (adaptive land use management), and anticipating and understanding future land use uncertainties e.g., the need to increase water availability – a limited resource – in a scenario of regional food security, or the need to strengthen urban containment policies in a scenario of farming under urban pressure.

This is the last chapter of this thesis, and the main purpose was to highlight the outcomes obtained in the different methodological approaches, to identify LUCC in different scenarios, and to recognise how LUCC models can be applied to support spatial planning instruments at the local level.

In the next section of this thesis, a general conclusion, the PhD thesis contribution, limitations, and future work will be drawn. Furthermore, the research questions and hypothesis of this PhD research will be evaluated.

Conclusion PART THREE

The discussion presented in Part three was undertaken to address the gaps between complexity and spatial planning. In this last Part, we demonstrated, as many researchers have discussed, the importance of integrating the views of private landowners and stakeholders into spatial planning decisions (Brown et al., 1981). They are a vital part of the process of improving spatial planning instruments. We discussed: a) how the LUCC models can help to solve planning issues; b) how LUCC models can be useful to understand better and manage critical demographic, social and economic issues; c) how LUCC models can provide solutions to spatial planning instruments; and d) how LUCC models can be valuable to create sustainable development strategies anticipating and understanding future land use uncertainties.

The urban growth in peri-urban regions and its direct impacts on the agricultural land decrease and fragmentation is contrary to the principles of sustainability. Tracking the changes is essential to identify these dynamics. New approaches were proposed. The analysis presented in this last Part highlights farmers' LUCC intentions in a business-as-usual scenario, in a regional food security, in a climate change, and in a farming under urban pressure scenario. We have introduced a methodology to better understand land-use dynamics to explain and discuss the impacts of farmers' decisions on land use transformation. The results achieved using the CA-Markov and ANN-MLP methods showed an increase of permanently irrigated land and a decrease of pastures in the A1 scenario; a drop in non-irrigated arable land and permanently irrigated land in the A2 scenario; and an increase of artificial surfaces, and a higher decrease of pastures in the B0 scenario.

The analysis of these results in the participatory workshop, allowed to identify better practices that can be taken into the realm of spatial planning policies.

General Conclusion

This PhD research presents a step forward methodology, demonstrating a complex interrelationship analysis between individuals and their behaviours and the external environment. This research has discussed a methodological approach to be integrated into land-use planning processes and is organised into three main parts with seven chapters.

Part One is a revision of the state of art of this PhD research with theoretical background about LUCC, modelling and spatial planning. It is subdivided into three chapters (chapter one, chapter two, and chapter three). Chapter one presents a literature review of preceding research work on agricultural land use and peri-urbanisation, its drivers and impacts. Chapter two depicts a literature review of geographic modelling, complexity and land use. And chapter three is regarding how land use planning and LUCC modelling can be integrated.

Part Two – Measuring LUCC in Torres Vedras (Portugal) is divided into two chapters (chapter four and chapter five). Chapter four describes the land use, driving forces, and the data management of the case study. Chapter five presents the empirical study about the influence of urban growth on agricultural land evolution and a method to analyse agricultural land fragmentation.

Part three – Integrating farmers' LUCC intentions in LUCC modelling process and engaging stakeholders' in the LUCC modelling process is divided into two chapters (chapter six and chapter seven). Chapter six is one of the main chapters of this thesis, in which is described every step to model LUCC using farmers' LUCC intentions, applied to four scenarios, and using three different methods. Chapter seven discusses the LUCC models outcomes. This task demonstrated the importance of integrating mixed methods in the decision-making process. Moreover, we also pointed out some policy recommendations.

The primary concern of this thesis was to describe and to evaluate the impacts of farmers' LUCC intentions according to different scenarios in a peri-urban region. This research arises from the current relevance of agricultural land preservation, the necessity for a more sustainable urban development, and the need for more efficient local and regional policies.

One of the potential threats of land-use sustainability is the conversion from agriculture land into artificial surfaces. In this PhD research, we addressed different approaches to answering the proposed hypotheses.

The first hypothesis that urban growth has a significant impact on agricultural land decrease and fragmentation was accepted. Based on this hypothesis it can be concluded that urban growth had severe impacts on agricultural land decrease and agricultural land fragmentation increase. However, we also verified, through LAND method, that urban growth occurred near to the existing urban areas. In our findings, we corroborated the 'first law' of geography (Tobler, 1969) and the theory of spatial dependence, in which a high urban containment, coalescence, and reducing discontinuity was verified. These results are in line with Fertner et al. (2016), and Jehling et al. (2016).

The second hypothesis that social, demographic, economic, and political drivers affect farmers' LUCC intentions in different scenarios, was accepted. We concluded that drivers such as for emotional reasons or land use regulations can be decisive in the LUCC conversion. We also found that economic drivers can be critical. Thus, from farmers' interviews we captured the following economic drivers that can be decisive: in A1 scenario - the increase of European funds and increase of production costs; in A2 scenario - the decrease of European funds; and in B0 scenario - the increase of urban land prices.

Moreover, other demographic, economic, and political drivers were also recognised as the main responsible for LUCC according to the LUCC models' results. According to the CA-Markov and ANN-MLP - LUCC models the driving forces that most influence artificial surfaces growth were population density, dwelling, buildings, and distance to urban areas; and in the CA-Markov for all agricultural land use classes were those related to distance to agricultural land, distance to coastline, slope, and agricultural land use protection (RAN).

The third hypothesis that the stakeholder's engagement in the criticism of LUCC models' outcomes may be the key to propose land use planning recommendations more efficiently was accepted. However, while stakeholders' analysis was recognised appropriate to reach consensus, emphasising the significance of the participatory workshop, we think that more needs to be done, namely in incorporating this analysis into the policies and spatial planning instruments to improve land-use strategies.

Land use strategies should find a balance between economic growth and agricultural protection (Martín-Retortillo and Pinilla 2015; Xuezhenet et al. 2010). Several studies – e.g., Lovell (2010), Parker (2007), Vagneron (2007) – have suggested that agricultural policies should contribute to reducing human impacts on the local and regional ecosystems. A decision support system to define land use strategies should identify where, when, what, and how much land should be used for a specific purpose. Therefore, measures to mitigate agricultural conversion to other uses, as well as to mitigate agricultural land fragmentation, it is required to inform decision-makers, preventing land degradation, e.g., Alfiky et al. (2012), and allowing a better understanding of the mechanisms for different responses.

In Torres Vedras (Portugal), the last two decades were characterised by progressive urbanisation resulting in a decrease of permanent crops, heterogeneous agricultural land, and pasture. In this research, we verified how demographic, economic and environmental factors could affect farmer's intentions on future agricultural LUCC. Farmers balanced costs and benefits while deciding to maintain, abandon, expand or sell to agricultural or urban use. We demonstrated how farmer age is another critical factor for LUCC decisions since younger farmers are more open to change their economic activity. In the B0 scenario, the youngest farmers are happy to sell their current farmland and to buy a new farm in another place, preferably in Torres Vedras if there is an economic advantage. Older farmers may be less willing to change for emotional reasons such as shown by Fazal et al. (2015). Older farmers wish to leave their farmland to their descendants, and they considered that their advanced age inhibits them from reinvesting in another location. According to the achieved results in Torres Vedras a dynamic monitoring system of land utilisation should be settled according to each scenario:

a) In the A1 scenario, in which was registered the highest demand for permanently irrigated land, measures should be considered to improve irrigation systems to make the farmers more efficient and competitive, e.g. Levidow et al. (2014), and Holzapfel et al. (2009). This was one of the main solutions pointed by the stakeholders in the participatory workshop;
b) In the A2 scenario, was registered the higher growth in the forest and semi-natural areas. Currently, in our case study, more than 80% of the forest is eucalyptus - non-Mediterranean tree. In this case, land use recommendations should focus on the creation

of incentive programs to promote the planting of Mediterranean trees, as suggested by Brundu and Richardson (2016), and Vallejo (2005).

c) In the B0 scenario, the greatest urban growth is verified. Urban containment and agricultural protection policies should be strengthened/applied more effectively given the major urban growth that might occur, as suggested by Bengston and Youn (2006), Cheshire (2009), and Salvati et al. (2018).

The integration of complexity science into the spatial planning process is something that needs to be applied. This integration can help to reduce the slowness of the analysis among the demographic, economic and LUCC transformations and the application of land protection tools. This integration can help, in addition, to analyse these transformations in a more efficient way, finding a better balance between the population needs and environmental protections.

Regarding the spatial planning instruments, where these analyses could be integrated, beyond the Municipal Master Plan (PDM) (with the limitation to be applied singly to one municipality), plans such as the Inter-municipal plans (PIOT), could be a better way to analyse and understand the land transformations at a larger scale. The focus could be not limited to one municipality but in a more inclusive perspective between one municipality and their neighbours, because sometimes the transformations are not limited to the border of one municipality (but a set of them). The application of PIOT in Portugal, although they are provided by law, they are not yet effectively applied in the Portuguese spatial planning process.

Medium-long-term perspectives

In recent years, Lisbon has seen major changes in the housing stock. Political measures such as the amendment on housing rental law (which facilitate the eviction of tenants); the golden visa (which allow a non-EU citizen to purchase a real estate property with a value equal to or above 500 thousand Euros, and then to obtain a granting of Residence Permit); the tax-free for retirement income for people non-habitual residency in Portugal; or the growth of tourism in Lisbon in recent years (which have been transformed the long-term rental houses into short-term rental), have been led to an increase in house prices.

Therefore, the high prices of housing in Lisbon, have been increased the demand for housing demand outside the city by residents, which have been leading to a price-spreading effect. This makes the municipality of Torres Vedras (located roughly 50 km north), one of the potential targets in the demand for housing by new residents.

Beyond this recent phenomenon, we think that in a medium-long-term period, there are other factors that can lead to an increase in housing demand in areas like Torres Vedras, such as the evolution of information technology. In recent years more people can work from home. They can benefit from the proximity of Lisbon, but they do not need to commute daily to Lisbon. Another fact, we believe can increase the housing demand by new residents, will be the electric cars. Although the incontestable benefits that these vehicles have in the greenhouse effect (zero-emission), we think, due to the low cost of charging, they indirectly can promote the increase of extensive urbanization. People will be able to commute low cost in long distances, and the demand for single-family homes can increase.

In addition, to the amenities that Torres Vedras benefit for having mixed urban and rural uses, it benefits for being bathed (in 20 km) by the Atlantic Ocean. The coast of Torres Vedras is one of the main tourist hotspots in the municipality. The locality of Santa Cruz (at Silveira parish) is well-known for their beaches and for practice surfing (in 2018, Santa Cruz was home to one of the stages of the World Surf League). Some hotels on the coast, such as the Areias do Seixo (opened in 2010) and the Noah Surf House Portugal (opened in 2018), the quality of the beaches (in 2019, 11 beaches were distinguished with Blue Flag) and the natural landscapes of Torres Vedras, have given some national and international notoriety in recent years. These are good indicators for the touristic sector, however, these attraction spots can create some disequilibrium in the protection of natural and agricultural land, especially near the coast where the soils are more fertile, and the agricultural productivity is higher. These dichotomies create new challenges for planners, especially when agriculture is an important contributor to the local economy. In addition, to reinforce the importance of this economic activity, recently (in 2018) Torres Vedras received the prize of the European Wine City.

These dynamics will create inevitably some LUCC. Some more expected than others, and some may occur in the next few years or in a medium-long term. Accordingly, we need to be prepared for these transformations.

From the artificial surfaces' growth perspective (for residential or tourism uses), and apart from the issues already discussed, the new built-up areas must have environmental concerns such as buildings with high energetic efficiency using renewable energies, green roofs, and environmentally friendly construction materials.

From the agricultural land perspective beyond the threat of urban pressure, the agricultural sector must be aware of global warming (with longer periods of drought and greater scarcity of water availability), and the need to change the production of certain crops. These readjustments can be also related to other causes, such as by the use of new technology, by the competition of other markets or even by the demand for new consumption patterns.

Modern technology has been increasing the quantity and quality of agricultural products in recent years. Smart farming is already a reality, and technology can improve even more agricultural production, using, for instance, unmanned tractors controlled via GPS, drones to kill vermin, and precision agriculture.

Farmers can also be faced by other challenges in the future such as the new alternatives of production and consumption, especially those that developed their economic activity in the vegetable sector. For instance, the production of vegetables cultivated at home or in the urban core, for self-consumption, or even the urban vertical farming, produced in buildings, in the urban core of the cities, can represent a competitive market for peri-urban farmers.

These political, environmental, demographic social and economic issues, will change the actual paradigm of farming in peri-urban areas in a near future, forcing farmers to be capable to readapt their production, according to the changes that may occur.

PhD thesis contributions

In the context of geospatial modelling, there is a broad of scientific-technological approaches. Along with this line of scientific background, this research is primarily committed to exploring the dynamics of LUCC based on farmers' intentions. Once the LUCC models performed to handle a comprehensive agricultural land use analysis, this study aims at opening up new methodological paths for further investigations. LUCC simulation experiments are dealing with different categories of land use that have been conducted by Parker et al. (2003), Lambin et al. (2003), and Valbuena et al. (2010a). While the LUCC predictions developed by these authors are generated upon exploratory techniques, the LUCC predictions performed in this PhD research are based upon on new narratives and storylines to understand LUCC dynamics through farmers' LUCC intentions. We presented a prospective approach to better understand spatial and temporal land-use dynamics, identifying what is more relevant in the decision process. The results achieved in this study should: (1) inform the policymakers and the community (demonstrating future land use alternatives and showing its impacts); (2) show the suitable land use options to avoid undesirable future impacts (adaptive land use management); and (3) simulates and predicts LUCC to support planners, to create sustainable development strategies, and to anticipate and to understand future land use uncertainties.

This PhD thesis has explored the potential for developing geospatial modelling. We integrated LUCC modelling (CA-Markov, ANN-MLP, and ABM) with a GIS-based methodology to support planning decisions at the local planning level. We aimed to understand how farmers' play in the decision-making process; to understand LUCC stakeholders' visions, and; verify How? Where? Why? and What land-use conversions may occur. As the main contribution, we intend to facilitate the communication and exchange of knowledge between farmers and decision-makers for framing the best political options for land use. Modelling LUCC is an effective way to integrate expert knowledge for evaluating land use alternatives.

Future uncertain and stochastic events can be unexpected. However, coherent and plausible land-use strategies can be applied to evaluate potential future impacts on land use (Rounsevell et al., 2006). We established how modelling LUCC could be successfully incorporated through land-use spatial planning. We point out a challenge facing to implement regulations in territorial management instruments and integrate farmers' LUCC intentions and stakeholders' visions into the realm of spatial planning practices.

This PhD research makes relevant contributions and encompasses several essential features. We lead to a better understanding and management of critical demographic, economic and environmental issues, to a better understanding regarding the preservation and maintenance of farming in peri-urban areas, and we introduced advances in land-use modelling.

We believe that this PhD research is one step forward towards to better recognise the environmental landscape. It offers insights to land planners so that they can better manage the land (Li et al., 2016), identifying the driving forces that were, are, and will be responsible for LUCC. More studies on agricultural land change should be carried out to monitor its dynamics (spatially and temporally). It remains scant in the Portuguese context.

Implementing policies to preserve agricultural land needs to be done, and more laws for its protection must be passed in a timely manner (Abrantes et al., 2016; Gomes et al., 2018). In addition, this remark is especially relevant for our case study, once Torres Vedras is one of the major suppliers of fresh fruits, vegetables, and wine in Portugal (Statistics Portugal, 2011).

Limitations

During this PhD research, we confronted with several weaknesses in the data gathering, as well as the challenge of LUCC model analysis and validation. The difficulties arising from accurate data acquisition and finding appropriate models. Following, we detailed some of the main limitations of this research.

Due to limited available data, we think the calibration process was not long enough to detect satisfactory LUCC for longer predictions (a wider time-span would have been more proper). Also, during the progress of this PhD thesis, an updated land-use data for the year 2015 was developed and validated by DGT. However, we opted to use the year 2010 as the most updated land-use data. This mainly due the fact of the arable land use class in 2015 was not subdivided (between non-irrigated arable and permanently irrigated) as it was in the land use maps of 1995, 2007, and 2010. Nevertheless, we compared the agreement between land use map 2010 and 2015 using the Kappa index of agreement (KIA). As outcomes we obtained the following KIA values: artificial surfaces = 0.9658; arable land = 0.8026; permanent crops and heterogeneous agricultural = 0.8894; pastures = 0.7867; forest = 0.9278; and wetlands and water bodies = 0.8814. These values reveal high levels of agreement.

Regarding the LUCC models, although they can be of value, it is still difficult to communicate the outcomes to non-experts. Moreover, LUCC models have some weaknesses that must be addressed. Each model and each scenario employed is built on some hypotheses which might not represent the best choices. In addition, it will be important in further analysis to test the methodology applied in this research into other case studies. Modelling LUCC has also demonstrated to be useful for the identification of the main impacts on land conversion. However, there's still a gap between these models and local planning authorities to manage and reorganise land allocation priorities according to the environmental, demographic and economic needs.

Future work

This PhD research explored a methodological approach to support collaborative land use planning processes and examined the integration of spatial planning and complexity science. Although the results presented were effectively tested, several issues remain unexplored and can be addressed by future researches. More analyses need to be conducted. As future work, it can be recommended, e.g., (1) to gather detailed and updated land use data (using satellite images, for instance); (2) to analyse LUCC for a longer time horizon; (3) to apply other LUCC models (e.g., CLUE, DINAMICA, and Land Change Modeler) to test different statistical approaches; (4) to integrate other stakeholders (e.g., real estate developers, and foresters) to determine their LUCC intentions, in order to have a more comprehensive review of all future land use transformations intentions, which can help decision-makers in a better land management; (5) to test the proposed methodology for comparison in another study area to evaluate the replicability; and (6) regarding the FARMER model, we think is still a prototype, and some progress such as to improve the usability of the model, to allow to add other spatial factors and constraints, or even to allow the user to define their LUCC intentions for each land use class and scenario, are some developments which we think could be an advantage for the model.

In brief, the current PhD research is entrusted with providing methodological guidance for future scientific investigations. We believe this study will help, in future works, researchers, modellers and decision-makers to better visualise and evaluate the effects of future LUCC.

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Appendix I

```
extensions [GIS nw]

globals [road selection selection-remainder selection-stable selection-other changes-tested? ]

patches-own
[
  landuse_date1
  landuse_date2
  variable-to-map
  tagged-as-neighboor?
]
;*************************
;Load File and display map
;*************************

to load-file-date1
 print "Importing Landuse"
let file user-file
file-open file
foreach sort patches [ ?1 -> ask ?1 [set landuse_date1 file-read ] ]
file-close
 end

 to load-file-date2
 print "Importing Landuse"
let file user-file
file-open file
foreach sort patches [ ?1 -> ask ?1 [set landuse_date2 file-read ] ]
file-close
 end



 to load-file
   ifelse LandUse-Date = "Date1"
  [
    load-file-date1
  ]
  [
    load-file-date2
  ]
 end


to setup-roads
  set road gis:load-dataset  user-file
gis:set-drawing-color black gis:draw road 2

end

 to setup
   reset-ticks
   set selection []
   set changes-tested? 0
   ask patches [set tagged-as-neighboor? 0]
 end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;LAND USE CHANGE Date 1-Date2;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to define-selection
 set selection patches with [landuse_date1 = LandUse-Date1 and landuse_date2 = LandUse-Date2]
end


to define-selection-remainder
 set selection-remainder patches with [landuse_date1 = LandUse-Date1 and landuse_date2 != LandUse-Date2 and landuse_date2 !=
LandUse-Date1]
end
```

```
to define-notchanging-patches-selection
 set selection-stable patches with [landuse_date1 = LandUse-Date1 and landuse_date2 = LandUse-Date1]
end

to define-notchanging-patches
 set selection-other patches with [landuse_date1 != LandUse-Date1 and landuse_date1  = landuse_date2]
end

to tag-selection-neighborhoors
  ask selection
  [
    ask patches in-radius Neighboring-distance [set tagged-as-neighboor? 1]
  ]
end


to tag-selection-remainder-neighborhoors
  ask selection-remainder
  [
    ask patches in-radius Neighboring-distance with [tagged-as-neighboor? = 0] [set tagged-as-neighboor? 2]
  ]
end

to tag-selection-stable-neighborhoors
  ask selection-stable
  [
    ask patches in-radius Neighboring-distance with [tagged-as-neighboor? = 0] [set tagged-as-neighboor? 3]
  ]
end

to tag-selection-other-neighborhoors
  ask selection-other
  [
    ask patches in-radius Neighboring-distance with [tagged-as-neighboor? = 0] [set tagged-as-neighboor? 4]
  ]
end

to set-changes-date1-date2
  ask patches [set tagged-as-neighboor? 0]
  define-selection
  define-selection-remainder
  define-notchanging-patches
   define-notchanging-patches-selection
   map-changes
  set changes-tested? 1
  tag-selection-neighborhoors
  tag-selection-remainder-neighborhoors
 tick
  end


to map-changes
 ask patches [set pcolor grey]
 ask selection [set pcolor red] ; "LandUse-Date1 --> LandUse-Date2 (RED)"
 ask selection-remainder  [set pcolor green] ;"LandUse-Date1 --> Any other landuse - Date2 (GREEN)"
 ask selection-other [set pcolor white] ; stable patches with other LandUse-Date1
 ask selection-stable [set pcolor orange] ;"LandUse-Date1 --> LandUse-Date1 (ORANGE)"
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;MAP LAND USE;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to map-landuse

  ifelse LandUse-Date = "Date1"

     [
    ask patches
```

```
  [
  set variable-to-map landuse_date1
 ]]
 [
 ask patches
  [

  set variable-to-map landuse_date2
 ]]


 ask patches with [ variable-to-map = 1 ] [
  set pcolor red ]
 ask patches with [ variable-to-map = 2 ] [
  set pcolor yellow ]
 ask patches with [ variable-to-map = 3 ] [
  set pcolor 49 ]
 ask patches with [ variable-to-map = 4 ] [
  set pcolor 111 ]
 ask patches with [ variable-to-map = 5 ] [
  set pcolor orange ]
 ask patches with [ variable-to-map = 6 ] [
  set pcolor 128 ]
 ask patches with [ variable-to-map = 7 ] [
  set pcolor 67 ]
 ask patches with [ variable-to-map = 8 ] [
  set pcolor 86 ]
end
;;;;;;;;;;;;;;;;
;;;;LEGEND;;;;;;
;;;;;;;;;;;;;;;;

to-report %CultivatedLand  [variable]
 report count patches with [variable = 1] / Count patches * 100
end

to-report %uncultivatedLand [variable]
 report count patches with [variable = 2] / Count patches * 100
end

to-report %forestsareas [variable]
 report count patches with [variable = 3] / Count patches * 100
end

to-report %builtupareas [variable]
 report count patches with [variable = 4] / Count patches * 100
end

to-report %wetlandswaterbodies [variable]
 report count patches with [variable = 5] / Count patches * 100
end

to-report %roadnetwork [variable]
 report count patches with [variable = 6] / Count patches * 100
end

to-report %rivers [variable]
 report count patches with [variable = 7] / Count patches * 100
end

to-report %protectedareas [variable]
 report count patches with [variable = 8] / Count patches * 100
end

;;;;;;;;;;;;;;;
;;;;;END;;;;;;
;;;;;;;;;;;;;;;


;;Land-use

;-9999 = nodata
```

Appendix II

Standardized Coefficient Beta value. Independent variables (rows); landscape metrics using agricultural land use classes (1995 and 2010) (columns).

Independent variables: 1 – resident population (density); 2 – population of farmers (density); 3 – dwelling (density); 4 – buildings (density); 5 – agricultural area used (density); 6 – artificial surfaces (%); 7 – non-irrigated land (%); 8 – permanent irrigated land (%); 9 – permanent crops and heterogeneous agricultural land (%); 10 – forest (%); 11 – pastures (%); 12 – vineyards (%); 13 – road network (%); 14 – national agricultural reserve (%); 15 – national ecological reserve (%); 16 – non-aedificandi areas (%); 17 – urbanizable area (%); 18 – slope (average).

Land use classes: 2 - non-irrigated land; 3 - permanent irrigated land; 4 - permanent crops and heterogeneous agricultural land; and 5 - pastures). Landscape metrics: MPS, MPE, MSI, MESH, and PROX.

	MPS 2		MPE 2		MSI 2		MESH 2		PROX 2		MPS 3		MPE 3		MSI 3		MESH 3		PROX 3	
	95	10	95	10	95	10	95	10	95	10	95	10	95	10	95	10	95	10	95	10
1	0.38	0.53	0.20	0.65	-0.14	0.75	-0.26	-0.07	-0.66	0.21	0.04	0.13	0.05	0.14	-0.16	0.37	-0.12	0.14	-0.15	0.08
2	-0.39	-8.64	-0.25	-9.43	0.30	-8.86	-0.48	-9.19	-0.27	-9.49	0.08	0.53	0.18	-2.65	0.26	-11.10	-0.10	5.20	0.01	5.14
3	0.15	1.86	0.43	1.55	0.61	1.27	1.21	1.69	2.21	1.53	-0.18	2.04	-0.01	1.87	0.86	1.63	0.42	2.95	0.44	3.18
4	-0.85	-3.58	-1.19	-3.09	-1.70	-2.46	-1.60	-3.01	-2.37	-2.12	-0.55	-2.82	-0.59	-2.93	-0.72	-3.49	-1.35	-4.30	-1.35	-4.22
5		9.03		9.91		9.40		8.68		9.29		-0.39		2.66		10.97		-4.32		-4.32
6	-0.26	0.67	-0.42	0.37	-0.70	0.07	0.09	0.33	0.23	0.27	-0.49	-0.43	-0.49	-0.29	-0.21	0.52	-0.42	-0.24	-0.26	-0.36
7											-0.09	-0.73	-0.10	-0.89	-0.07	-0.87	-0.85	-0.40	-0.78	-0.44
8	-0.03	-0.30	-0.06	-0.17	-0.13	0.48	0.24	0.54	-0.03	0.00										
9	0.79	0.74	0.45	0.84	-0.88	1.46	0.57	0.10	-0.05	0.46	-1.22	-0.78	-1.14	-0.75	-0.14	-0.08	-1.46	-0.19	-1.43	-0.32
10	-0.33	-0.25	-0.43	0.06	-0.87	0.46	-0.71	-0.06	-1.11	-0.20	-0.87	-0.16	-0.82	-0.20	-0.38	-0.32	-1.76	-0.19	-1.81	-0.15
11	0.04	-0.71	0.00	-0.44	-0.11	0.48	-0.02	0.04	-0.03	-0.51	-0.03	-1.24	-0.05	-1.29	0.07	-1.11	-0.45	-0.91	-0.46	-0.97
12	-0.96	-2.71	-0.77	-2.48	-0.16	-2.12	-0.81	-0.47	-0.49	-1.64	0.05	-1.35	-0.04	-1.35	-0.43	-1.51	-0.28	-1.87	-0.32	-1.82
13	-0.37	-1.30	-0.19	-1.14	0.19	-0.91	-0.11	-1.21	-0.03	-1.02	-0.02	-0.56	-0.01	-0.37	-0.07	-0.21	0.33	-0.63	0.46	-0.60
14	-0.07	0.54	-0.21	0.36	-0.79	0.21	0.14	0.44	0.35	0.60	-0.11	0.63	-0.13	0.68	-0.04	0.68	-0.01	0.46	-0.07	0.49
15	-0.29	0.05	-0.32	0.06	-0.24	-0.04	-0.28	0.54	-0.30	-0.04	0.23	-0.24	0.27	-0.27	0.45	-0.33	-0.18	-0.36	-0.17	-0.43
16	0.86	1.38	0.70	1.31	0.54	1.26	0.40	0.61	-0.17	0.59	0.10	0.85	0.08	0.77	-0.40	0.84	0.26	1.57	0.23	1.42
17	0.10	0.42	0.26	0.40	0.59	0.33	-0.02	1.38	0.23	0.36	0.71	0.55	0.65	0.56	0.64	0.44	0.26	0.48	0.01	0.46
18	0.33	0.59	0.13	0.50	-0.53	0.52	0.66	0.35	0.57	0.67	-0.41	0.36	-0.48	0.48	-0.50	0.76	0.47	0.13	0.48	0.23

	MPS 4		MPE 4		MSI 4		MESH 4		PROX 4		MPS 5		MPE 5		MSI 5		MESH 5		PROX 5	
	95	10	95	10	95	10	95	10	95	10	95	10	95	10	95	10	95	10	95	10
1	0.28	0.92	0.28	1.13	0.30	1.51	-0.13	-0.35	-0.18	-0.34	0.09	1.18	-0.13	0.82	-0.31	1.13	0.26	0.87	0.35	1.35
2	0.09	-10.5	0.34	-12.3	0.22	-11.7	0.08	-2.93	0.04	-2.05	-0.62	-6.19	-0.72	-2.85	-0.70	2.70	0.70	-15.7	0.94	-4.85
3	1.14	0.23	0.98	-0.51	0.28	-0.89	-0.21	-1.25	0.23	-1.14	-0.08	-1.54	0.40	-1.58	0.61	-1.95	-0.21	-2.28	-0.06	-0.13
4	-1.46	-1.52	-1.68	-1.12	-1.26	-1.00	-0.02	0.81	0.01	0.79	-0.20	-0.12	-0.62	0.28	-0.94	1.91	0.07	-0.32	-0.09	-0.36
5		10.7		12.7		12.1		3.16		2.22		7.88		4.18		-3.37		18.25		4.42
6	-0.03	-0.27	0.05	-0.24	0.32	0.00	0.24	0.27	0.41	0.28	-1.11	-0.06	-1.05	-0.27	-0.73	-0.42	-1.58	-2.43	-0.81	1.45
7	-1.41	-1.50	-1.23	-1.17	-0.21	-0.82	-0.99	-0.14	-1.42	-0.28	-1.57	-0.48	-0.90	-0.51	0.09	-0.28	-3.66	-4.73	-1.95	-0.61
8	-1.28	-1.02	-1.38	-0.81	-0.56	-0.40	-0.71	-0.24	-0.96	-0.35	-1.45	-2.43	-0.57	-2.70	0.75	-0.84	-4.78	-11.8	-3.46	1.67
9											-2.33	-3.22	-1.66	-3.81	-0.41	-1.98	-4.72	-11.9	-2.82	4.71
10	-1.74	0.06	-1.73	0.27	-0.74	0.43	-1.11	-0.02	-1.51	-0.03	-2.58	-1.72	-1.70	-2.29	-0.15	-1.31	-5.59	-11.4	-3.87	1.70
11	-0.22	-0.84	-0.14	-0.19	0.11	0.18	-0.50	0.15	-0.56	-0.04										
12	-0.78	-0.73	-0.99	-0.28	-0.84	-0.76	0.02	1.59	-0.42	1.39	0.55	1.11	0.70	1.63	0.86	0.47	-0.37	3.51	-1.36	-4.67
13	-0.42	-0.68	-0.32	-0.44	-0.02	-0.71	0.22	0.85	-0.67	0.65	0.20	0.18	0.81	0.59	1.21	0.03	-0.46	1.16	0.16	-2.58
14	0.35	0.63	0.18	0.38	-0.14	0.56	0.23	-0.46	0.51	-0.35	-0.05	-0.70	-0.10	-0.82	-0.41	0.83	0.20	-2.39	0.60	2.74
15	-0.12	-0.32	0.05	-0.31	0.48	-0.19	0.16	0.39	0.11	0.40	0.01	-0.03	0.08	0.04	0.23	-0.61	-0.33	0.86	0.30	-0.39
16	0.28	1.26	0.33	1.29	0.02	1.16	0.23	-0.20	0.22	-0.18	0.18	0.66	-0.13	0.35	-0.21	-0.50	0.44	1.22	-0.05	0.87
17	0.10	0.19	0.13	0.14	0.05	0.27	-0.56	-0.61	-0.35	-0.51	0.23	-0.07	-0.03	-0.29	-0.31	-0.36	0.45	-0.49	-0.02	0.51
18	0.32	0.62	0.11	0.50	-0.12	0.88	0.13	-0.89	0.21	-0.81	-0.11	-1.03	-0.02	-1.10	0.04	0.66	-0.33	-1.97	-0.12	1.98

Appendix III

Farmers' interview form

Question number/ variable	Profile	
	Date	
	Name	
1	Age	
2	Education	
	Mobile phone	
	E-mail	
3	Parish	
4	Do you benefit from subsidies? (e.g., CAP)	

Question number	Farm	
5	Farmland hectares	
6	Number of agricultural parcels	
7	Owner and/or tenant	

Question number	Farmlands' characterization based on the following LUC classes	(%)
8	Artificial surfaces	
9	Non-irrigated arable land	
10	Permanently irrigated land	
11	Permanent crops and heterogeneous agricultural land	
12	Pastures	
13	Forest and semi-natural areas	
14	Water bodies	

Question number	Future LUCC intentions I	A0	A1	A2	B0
15	Expand/ decrease the farmland (%)				
16	If expand, where?				
17	Distance from the current farmland (m)				
18	Distance from water bodies (m)?				
19	Distance from road network (m)?				

Question number	Future LUCC intentions II	A0	A1	A2	B0
20	Artificial surfaces				
21	Non-irrigated arable land				

22	Permanently irrigated land				
23	Permanent crops and heterogeneous agricultural land				
24	Pastures				
25	Forest and semi-natural areas				
26	Water bodies				

Question number	**Future LUCC intentions III**	**A0**	**A1**	**A2**	**B0**
27	To sell the farmland? (%)				
28	If yes: artificial surfaces? (%); agricultural areas? (%); forest and semi-natural areas? (%)				
29	Abandon? (%)				

Thank you for your cooperation.

Appendix IV

```
patches-own [landuse modified-landuse no-building-areas road-network slope]

;*************************
;Load File
;*************************

to load-file-landuse
 print "Importing landuse"
let file user-file
file-open file
foreach sort patches [ ?1 -> ask ?1 [set landuse file-read ] ]
file-close
 end

 to load-file-no-building-areas
 print "Importing no-building-areas"
let file user-file
file-open file
foreach sort patches [ ?1 -> ask ?1 [set no-building-areas file-read ] ]
file-close
 end

to load-file-road-network
 print "Importing road-network"
let file user-file
file-open file
foreach sort patches [ ?1 -> ask ?1 [set road-network file-read ] ]
file-close
 end

to load-file-slope
 print "Importing slope"
let file user-file
file-open file
foreach sort patches [ ?1 -> ask ?1 [set slope file-read ] ]
file-close
 end

 to load-file
   If Raster = "landuse"
  [
    load-file-landuse
  ]
  if Raster = "no-building-areas"
  [
    load-file-no-building-areas
  ]
  if Raster = "road-network"
  [
    load-file-road-network
  ]
  if Raster = "slope"
  [
    load-file-slope
  ]
  end

to reset-landuse
ask patches
[set modified-landuse landuse]
map-landuse
reset-ticks
end

to setup-environment
load-file
reset-landuse
reset-ticks
  end

;*************************
```

```
;Patches - and display map
;************************

to map-landuse
  ask patches with [ modified-landuse = 1 ] [
    set pcolor [168 0 0] ]
  ask patches with [ modified-landuse = 2 ] [
    set pcolor [211 255 190] ]
  ask patches with [ modified-landuse = 3 ] [
    set pcolor [230 230 0] ]
  ask patches with [ modified-landuse = 4 ] [
    set pcolor [168 112 0] ]
  ask patches with [ modified-landuse = 5 ] [
    set pcolor [255 235 175] ]
  ask patches with [ modified-landuse = 6 ] [
    set pcolor [56 168 0] ]
  ask patches with [ modified-landuse = 7 ] [
    set pcolor [56 168 0] ]
  ask patches with [ modified-landuse = 98 ] [
    set pcolor white ]
  ask patches with [ modified-landuse = 99 ] [
    set pcolor blue ]
 end

;;landuse legend
;;1 = artificial surfaces
;;2 = non-irrigated arable land
;;3 = permanent irrigated land
;;4 = permanent crops and heterogeneous agricultural land
;;5 = pastures
;;6 = forest and semi-natural areas
;;7 = water bodies
;;98 = Outside Torres Vedras
;;99 = Atlantic Ocean


to no-building-areas1
  ask patches with [ no-building-areas = 0 ] [
    set pcolor gray ]
  ask patches with [ no-building-areas = 1 ] [
    set pcolor green ]
  ask patches with [ no-building-areas = 98 ] [
    set pcolor white ]
  ask patches with [ no-building-areas = 99 ] [
    set pcolor blue ]
  end

;;no-building-areas legend
;;No building areas legend
;;0 = Building areas [gray]
;;1 = No Building areas [green]
;;98 = Outside Torres Vedras [white]
;;99 = Atlantic Ocean [blue]


to road
  ask patches with [ road-network = 0 ] [
    set pcolor gray ]
    ask patches with [ road-network = 1 ] [
    set pcolor black ]
  ask patches with [ road-network = 98 ] [
    set pcolor white ]
  ask patches with [ road-network = 99 ] [
    set pcolor blue ]
  end

;;Road Network legend
;;0 = No Road Network [gray]
;;1 = Road Network [black]
;;98 = Outside Torres Vedras [white]
;;99 = Atlantic Ocean [blue]
```

```
to slope1
 ask patches with [ slope = 0 ] [
  set pcolor gray ]
 ask patches with [ slope = 1 ] [
  set pcolor yellow ]
 ask patches with [ slope = 2 ] [
  set pcolor orange ]
 ask patches with [ slope = 3 ] [
  set pcolor red ]
 ask patches with [ slope = 4 ] [
  set pcolor black ]
 ask patches with [ slope = 98 ] [
  set pcolor white ]
 ask patches with [ slope = 99 ] [
  set pcolor blue ]
  end

;;Slope legend
;;0 = 0º - Slope [gray]
;;1 = >0º - 5º=< - Slope [black]
;;2 = >5º - 10º=< - Slope [gray]
;;3 = >10º - 15º=< - Slope [black]
;;4 = >15º - 20º< - Slope [black]
;;98 = Outside Torres Vedras [white]
;;99 = Atlantic Ocean [blue]

 ;****************************
 ;      Scenario A0        ;
 ;****************************

to scenario_A0
  urb0-A0
  urb10-A0
  urb20-A0
  urb30-A0
  urb40-A0
  urb50-A0
  forest-to-agriculture-A0
  slope-farming-0-10-A0
  for0-A0
  for10-A0
  for20-A0
  for30-A0
  for40-A0
  for50-A0
  tick
  if ticks = 1 [stop]
end

;;;;;;;;;;;;;;;;;;;;;;;;;
;    SCENARIO A0     ;
;;;;;;;;;;;;;;;;;;;;;;;;;

;; Scenario A0 - Class 1 - artificial surfaces

to urban-A0-0
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A0 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A0 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A0 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A0 * 100 < Dens-urb-A0
and
random-float 1 < 0 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
```

```
]
end

to urban-A0-10
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A0 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A0 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A0 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A0 * 100 < Dens-urb-A0
and
random-float 1 < 0.1 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A0-20
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A0 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A0 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A0 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A0 * 100 < Dens-urb-A0
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A0-30
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A0 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A0 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A0 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A0 * 100 < Dens-urb-A0
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A0-40
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A0 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A0 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A0 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A0 * 100 < Dens-urb-A0
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end
```

```
to urban-A0-50
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A0 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A0 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A0 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A0 * 100 < Dens-urb-A0
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urb0-A0
If UrbanA0 = "0%"
[
Urban-A0-0
]
end

to urb10-A0
If UrbanA0 = "10%"
[
Urban-A0-10
]
end

to urb20-A0
If UrbanA0 = "20%"
[
Urban-A0-20
]
end

to urb30-A0
If UrbanA0 = "30%"
[
Urban-A0-30
]
end

to urb40-A0
If UrbanA0 = "40%"
[
Urban-A0-40
]
end

to urb50-A0
If UrbanA0 = "50%"
[
Urban-A0-50
]
end


;; Scenario A0 - Class 2 - non-irrigated arable land

to scenario_A0_class2
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.006 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
```

```
   ]
end

to scenario_A0_class2_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.006 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end

to scenario_A0_class2_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.006 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end


;; Scenario A0 - Class 3 - permanently irrigated land

to scenario_A0_class3
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5]
   [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < 0.2 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end

to scenario_A0_class3_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5  and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < 0.2 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end

to scenario_A0_class3_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6  and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < 0.2 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end


;; Scenario A0 - Class 4 - permanent crops and heterogeneous agricultural land
```

```
to scenario_A0_class4
ask patches with [modified-landuse = 2  or modified-landuse = 3  or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 4]
   and
   random-float 1 < 0.1 ;; Farmers' LUCC intentions
   [
   set modified-landuse  4
   set pcolor 32]
   ]
end

to scenario_A0_class4_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 4]
   and
   random-float 1 < 0.1 ;; Farmers' LUCC intentions
   [
   set modified-landuse  4
   set pcolor 32]
   ]
end

to scenario_A0_class4_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope = 
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 4]
   and
   random-float 1 < 0.1 ;; Farmers' LUCC intentions
   [
   set modified-landuse  4
   set pcolor 32]
   ]
end


;; Scenario A0 - Class 5 - Pastures

to scenario_A0_class5
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4]
  [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < -0.06 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

to scenario_A0_class5_slope_0_10 ;; Slope for farming : 5-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4  and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < -0.06 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

to scenario_A0_class5_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 6 and slope = 0 and slope = 
1 and slope = 2]
  [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < -0.06 ;; Farmers' LUCC intentions
```

```
  [
  set modified-landuse  5
  set pcolor 28]
  ]
end

;; Scenario A0 - Class 6 - Forest and semi-natural areas

to forest-A0-0
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0 ;; Users’ LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A0-10
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.1 ;; Users’ LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A0-20
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.2 ;; Users’ LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A0-30
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.3 ;; Users’ LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A0-40
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.4 ;; Users’ LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A0-50
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
```

```
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to for0-A0
If ForestA0 = "0%"
[
forest-A0-0
]
end

to for10-A0
If ForestA0 = "10%"
[
forest-A0-10
]
end

to for20-A0
If ForestA0 = "20%"
[
forest-A0-20
]
end

to for30-A0
If ForestA0 = "30%"
[
forest-A0-30
]
end

to for40-A0
If ForestA0 = "40%"
[
forest-A0-40
]
end

to for50-A0
If ForestA0 = "50%"
[
forest-A0-50
]
end

to f_A0
If ForestA0 = "0%"
[
forest-A0-0
]
If ForestA0 = "10%"
[
forest-A0-10
]
if ForestA0 = "20%"
[
forest-A0-20
]
if ForestA0 = "30%"
[
forest-A0-30
]
if ForestA0 = "40%"
[
forest-A0-40
```

```
]
if ForestA0 = "50%"
[
forest-A0-50
]
end


;*************************************************
;    conversion from forest to agriculture?  A0 ;
;*************************************************
to convert-forest-to-agriculture-A0
scenario_A0_class2_forest_to_agriculture
scenario_A0_class3_forest_to_agriculture
scenario_A0_class4_forest_to_agriculture
scenario_A0_class5_forest_to_agriculture
end

to not-convert-forest-to-agriculture-A0
scenario_A0_class2
scenario_A0_class3
scenario_A0_class4
scenario_A0_class5
end

to forest-to-agriculture-A0
  ifelse Forest-A0?
  [convert-forest-to-agriculture-A0]
  [not-convert-forest-to-agriculture-A0]
end


;**************************************
 ;      slope farming 0-10   A0 ;
 ;**************************************
to slope-farming-0-10-yes-A0
scenario_A0_class2_slope_0_10
scenario_A0_class3_slope_0_10
scenario_A0_class4_slope_0_10
scenario_A0_class5_slope_0_10
end

to slope-farming-0-10-no-A0
scenario_A0_class2
scenario_A0_class3
scenario_A0_class4
scenario_A0_class5
end

to slope-farming-0-10-A0
  ifelse A0-0-10º?
  [slope-farming-0-10-yes-A0]
  [slope-farming-0-10-no-A0]
end



 ;****************************
 ;      Scenario A1        ;
 ;****************************

to scenario_A1
  urb0-A1
  urb10-A1
  urb20-A1
  urb30-A1
  urb40-A1
  urb50-A1
  forest-to-agriculture-A1
  slope-farming-0-10-A1
```

```
 for0-A1
 for10-A1
 for20-A1
 for30-A1
 for40-A1
 for50-A1
 tick
 if ticks = 1 [stop]
end

;;;;;;;;;;;;;;;;;;;;;;;;
;    SCENARIO A1    ;
;;;;;;;;;;;;;;;;;;;;;;;;

;; Scenario A1 - Class 1 - artificial surfaces

to urban-A1-0
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A1 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A1 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A1 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A1 * 100 < Dens-urb-A1
and
random-float 1 < 0 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A1-10
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A1 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A1 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A1 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A1 * 100 < Dens-urb-A1
and
random-float 1 < 0.1 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A1-20
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A1 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A1 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A1 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A1 * 100 < Dens-urb-A1
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A1-30
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
```

```
if any? patches in-radius D-to-RN-urb-A1 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A1 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A1 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A1 * 100 < Dens-urb-A1
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A1-40
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A1 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A1 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A1 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A1 * 100 < Dens-urb-A1
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A1-50
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A1 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A1 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A1 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A1 * 100 < Dens-urb-A1
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urb0-A1
If UrbanA1 = "0%"
[
Urban-A1-0
]
end

to urb10-A1
If UrbanA1 = "10%"
[
Urban-A1-10
]
end

to urb20-A1
If UrbanA1 = "20%"
[
Urban-A1-20
]
end

to urb30-A1
If UrbanA1 = "30%"
[
```

```
Urban-A1-30
]
end

to urb40-A1
If UrbanA1 = "40%"
[
Urban-A1-40
]
end

to urb50-A1
If UrbanA1 = "50%"
[
Urban-A1-50
]
end


;; Scenario A1 - Class 2 - non-irrigated arable land

to scenario_A1_class2
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.03 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end

to scenario_A1_class2_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.03 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end

to scenario_A1_class2_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.03 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end


;; Scenario A1 - Class 3 - permanently irrigated land

to scenario_A1_class3
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5]
   [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < 0.68 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
```

```
end

to scenario_A1_class3_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5  and slope = 0 and slope = 1 and slope = 2]
 [
  if any? patches in-radius 5 with [modified-landuse = 3]
  and
  random-float 1 < 0.68 ;; Farmers' LUCC intentions
  [
  set modified-landuse  3
  set pcolor 43]
  ]
end

to scenario_A1_class3_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6  and slope = 0 and slope = 1 and slope = 2]
 [
  if any? patches in-radius 5 with [modified-landuse = 3]
  and
  random-float 1 < 0.68 ;; Farmers' LUCC intentions
  [
  set modified-landuse  3
  set pcolor 43]
  ]
end


;; Scenario A1 - Class 4 - permanent crops and heterogeneous agricultural land

to scenario_A1_class4
ask patches with [modified-landuse = 2  or modified-landuse = 3  or modified-landuse = 5]
  [
  if any? patches in-radius 5 with [modified-landuse = 4]
  and
  random-float 1 < 0.71 ;; Farmers' LUCC intentions
  [
  set modified-landuse  4
  set pcolor 32]
  ]
end

to scenario_A1_class4_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
 [
  if any? patches in-radius 5 with [modified-landuse = 4]
  and
  random-float 1 < 0.71 ;; Farmers' LUCC intentions
  [
  set modified-landuse  4
  set pcolor 32]
  ]
end

to scenario_A1_class4_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope = 1 and slope = 2]
 [
  if any? patches in-radius 5 with [modified-landuse = 4]
  and
  random-float 1 < 0.71 ;; Farmers' LUCC intentions
  [
  set modified-landuse  4
  set pcolor 32]
  ]
end


;; Scenario A1 - Class 5 - Pastures

to scenario_A1_class5
```

```
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4]
  [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < -0.25 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

to scenario_A1_class5_slope_0_10 ;; Slope for farming : 5-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4  and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < -0.25 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

to scenario_A1_class5_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < -0.25 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

;; Scenario A1 - Class 6 - Forest and semi-natural areas

to forest-A1-0
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A1-10
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.1 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A1-20
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
```

```
]
end

to forest-A1-30
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A1-40
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A1-50
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to for0-A1
If ForestA1 = "0%"
[
forest-A1-0
]
end

to for10-A1
If ForestA1 = "10%"
[
forest-A1-10
]
end

to for20-A1
If ForestA1 = "20%"
[
forest-A1-20
]
end

to for30-A1
If ForestA1 = "30%"
[
forest-A1-30
]
end

to for40-A1
If ForestA1 = "40%"
[
forest-A1-40
```

```
]
end

to for50-A1
If ForestA1 = "50%"
[
forest-A1-50
]
end

to f_A1
If ForestA1 = "0%"
[
forest-A1-0
]
If ForestA1 = "10%"
[
forest-A1-10
]
if ForestA1 = "20%"
[
forest-A1-20
]
if ForestA1 = "30%"
[
forest-A1-30
]
if ForestA1 = "40%"
[
forest-A1-40
]
if ForestA1 = "50%"
[
forest-A1-50
]
end

;**********************************************
;   conversion from forest to agriculture?  A1 ;
;**********************************************
to convert-forest-to-agriculture-A1
scenario_A1_class2_forest_to_agriculture
scenario_A1_class3_forest_to_agriculture
scenario_A1_class4_forest_to_agriculture
scenario_A1_class5_forest_to_agriculture
end

to not-convert-forest-to-agriculture-A1
scenario_A1_class2
scenario_A1_class3
scenario_A1_class4
scenario_A1_class5
end

to forest-to-agriculture-A1
  ifelse Forest-A1?
  [convert-forest-to-agriculture-A1]
  [not-convert-forest-to-agriculture-A1]
end


;***********************************
 ;      slope farming 0-10   A1 ;
 ;***********************************
to slope-farming-0-10-yes-A1
scenario_A1_class2_slope_0_10
scenario_A1_class3_slope_0_10
scenario_A1_class4_slope_0_10
scenario_A1_class5_slope_0_10
end
```

```
to slope-farming-0-10-no-A1
scenario_A1_class2
scenario_A1_class3
scenario_A1_class4
scenario_A1_class5
end

to slope-farming-0-10-A1
 ifelse A1-0-10º?
 [slope-farming-0-10-yes-A1]
 [slope-farming-0-10-no-A1]
end

;****************************
;      Scenario A2        ;
;****************************

to scenario_A2
 urb0-A2
 urb10-A2
 urb20-A2
 urb30-A2
 urb40-A2
 urb50-A2
 forest-to-agriculture-A2
 slope-farming-0-10-A2
 for0-A2
 for10-A2
 for20-A2
 for30-A2
 for40-A2
 for50-A2
 tick
 if ticks = 1 [stop]
end


;;;;;;;;;;;;;;;;;;;;;;
;    SCENARIO A2    ;
;;;;;;;;;;;;;;;;;;;;;;

;; Scenario A2 - Class 1 - artificial surfaces

to urban-A2-0
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A2 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A2 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A2 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A2 * 100 < Dens-urb-A2
and
random-float 1 < 0 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A2-10
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A2 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A2 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A2 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A2 * 100 < Dens-urb-A2
and
random-float 1 < 0.1 ;; Users' LUCC intentions
```

```
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A2-20
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A2 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A2 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A2 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A2 * 100 < Dens-urb-A2
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A2-30
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A2 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A2 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A2 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A2 * 100 < Dens-urb-A2
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A2-40
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A2 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A2 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A2 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A2 * 100 < Dens-urb-A2
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A2-50
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A2 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A2 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A2 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A2 * 100 < Dens-urb-A2
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
```

```
]
end

to urb0-A2
If UrbanA2 = "0%"
[
Urban-A2-0
]
end

to urb10-A2
If UrbanA2 = "10%"
[
Urban-A2-10
]
end

to urb20-A2
If UrbanA2 = "20%"
[
Urban-A2-20
]
end

to urb30-A2
If UrbanA2 = "30%"
[
Urban-A2-30
]
end

to urb40-A2
If UrbanA2 = "40%"
[
Urban-A2-40
]
end

to urb50-A2
If UrbanA2 = "50%"
[
Urban-A2-50
]
end


;; Scenario A2 - Class 2 - non-irrigated arable land

to scenario_A2_class2
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < -0.46 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end

to scenario_A2_class2_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < -0.46 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end
```

```
to scenario_A2_class2_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < -0.46 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end


;; Scenario A2 - Class 3 - permanently irrigated land

to scenario_A2_class3
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < -0.17 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end

to scenario_A2_class3_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5  and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < -0.17 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end

to scenario_A2_class3_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6  and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < -0.17 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end


;; Scenario A2 - Class 4 - permanent crops and heterogeneous agricultural land

to scenario_A2_class4
ask patches with [modified-landuse = 2  or modified-landuse = 3  or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 4]
   and
   random-float 1 < -0.11 ;; Farmers' LUCC intentions
   [
   set modified-landuse  4
   set pcolor 32]
   ]
end

to scenario_A2_class4_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
```

```
 [
   if any? patches in-radius 5 with [modified-landuse = 4]
   and
   random-float 1 < -0.11 ;; Farmers' LUCC intentions
   [
   set modified-landuse  4
   set pcolor 32]
   ]
end

to scenario_A2_class4_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
 [
   if any? patches in-radius 5 with [modified-landuse = 4]
   and
   random-float 1 < -0.11 ;; Farmers' LUCC intentions
   [
   set modified-landuse  4
   set pcolor 32]
   ]
end


;; Scenario A2 - Class 5 - Pastures

to scenario_A2_class5
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4]
 [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < 5.6 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

to scenario_A2_class5_slope_0_10 ;; Slope for farming : 5-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4  and slope = 0 and slope = 1 and slope = 2]
 [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < 5.6 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

to scenario_A2_class5_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
 [
   if any? patches in-radius 200 with [modified-landuse = 5]
   and
   random-float 1 < 5.6 ;; Farmers' LUCC intentions
   [
   set modified-landuse  5
   set pcolor 28]
   ]
end

;; Scenario A2 - Class 6 - Forest and semi-natural areas

to forest-A2-0
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0 ;; Users' LUCC intentions
```

```
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A2-10
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.1 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A2-20
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A2-30
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A2-40
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A2-50
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to for0-A2
If ForestA2 = "0%"
[
forest-A2-0
]
```

```
end

to for10-A2
If ForestA2 = "10%"
[
forest-A2-10
]
end

to for20-A2
If ForestA2 = "20%"
[
forest-A2-20
]
end

to for30-A2
If ForestA2 = "30%"
[
forest-A2-30
]
end

to for40-A2
If ForestA2 = "40%"
[
forest-A2-40
]
end

to for50-A2
If ForestA2 = "50%"
[
forest-A2-50
]
end

to f_A2
If ForestA2 = "0%"
[
forest-A2-0
]
If ForestA2 = "10%"
[
forest-A2-10
]
if ForestA2 = "20%"
[
forest-A2-20
]
if ForestA2 = "30%"
[
forest-A2-30
]
if ForestA2 = "40%"
[
forest-A2-40
]
if ForestA2 = "50%"
[
forest-A2-50
]
end

;***********************************************
;   conversion of forest to agriculture?  A2 ;
;***********************************************
to convert-forest-to-agriculture-A2
scenario_A2_class2_forest_to_agriculture
scenario_A2_class3_forest_to_agriculture
scenario_A2_class4_forest_to_agriculture
```

```
scenario_A2_class5_forest_to_agriculture
end

to not-convert-forest-to-agriculture-A2
scenario_A2_class2
scenario_A2_class3
scenario_A2_class4
scenario_A2_class5
end

to forest-to-agriculture-A2
  ifelse Forest-A2?
  [convert-forest-to-agriculture-A2]
  [not-convert-forest-to-agriculture-A2]
end


;*************************************
 ;      slope farming 0-10   A2 ;
 ;*************************************
to slope-farming-0-10-yes-A2
scenario_A2_class2_slope_0_10
scenario_A2_class3_slope_0_10
scenario_A2_class4_slope_0_10
scenario_A2_class5_slope_0_10
end

to slope-farming-0-10-no-A2
scenario_A2_class2
scenario_A2_class3
scenario_A2_class4
scenario_A2_class5
end

to slope-farming-0-10-A2
  ifelse A2-0-10º?
  [slope-farming-0-10-yes-A2]
  [slope-farming-0-10-no-A2]
end


 ;****************************
 ;      SCENARIO A3
 ;****************************

;;to scenario_A3
;;  build-protected-areas-A3
;;  f_A3
;;  tick
;;  if ticks = 1 [stop]
;;end


 ;****************************
 ;      Scenario A3        ;
 ;****************************

to scenario_A3
  urb0-A3
  urb10-A3
```

```
 urb20-A3
 urb30-A3
 urb40-A3
 urb50-A3
 build-in-not-protected-areas-A3
 forest-to-agriculture-A3
 slope-farming-0-10-A3
 for0-A3
 for10-A3
 for20-A3
 for30-A3
 for40-A3
 for50-A3
 tick
 if ticks = 1 [stop]
end


;;;;;;;;;;;;;;;;;;;;;;
;    SCENARIO A3     ;
;;;;;;;;;;;;;;;;;;;;;;

;; Scenario A3 - Class 1 - artificial surfaces - ;; Users' LUCC intentions

to urban-A3-0
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A3-10
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.1 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A3-20
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  1
```

```
set pcolor 12]
]
end

to urban-A3-30
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A3-40
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urban-A3-50
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0 ]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1 and modified-landuse = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

to urb0-A3
If UrbanA3 = "0%"
[
Urban-A3-0
]
end

to urb10-A3
If UrbanA3 = "10%"
[
Urban-A3-10
]
end

to urb20-A3
If UrbanA3 = "20%"
```

```
[
Urban-A3-20
]
end

to urb30-A3
If UrbanA3 = "30%"
[
Urban-A3-30
]
end

to urb40-A3
If UrbanA3 = "40%"
[
Urban-A3-40
]
end

to urb50-A3
If UrbanA3 = "50%"
[
Urban-A3-50
]
end

;; Scenario A3 - Class 1 - artificial surfaces - ;; Farmers' LUCC intentions

to scenario_A3_class1
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6
and no-building-areas = 0]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.478 ;; Farmers' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end


to scenario_A3_class1_build_in_protected_areas ;; Build in protected areas?-A3scenario
ask patches with [modified-landuse = 2 or modified-landuse = 3  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6]
[
if any? patches in-radius D-to-RN-urb-A3 with [road-network = 1]
and
any? patches in-radius D-to-urb-A3 with [modified-landuse = 1]
and
count patches in-radius D-to-urb-A3 with [modified-landuse = 1] /  count patches in-radius D-to-urb-A3 * 100 < Dens-urb-A3
and
random-float 1 < 0.478 ;; Farmers' LUCC intentions
[
set modified-landuse  1
set pcolor 12]
]
end

 ;*************************************
 ;      build in protected areas  A3   ;
 ;*************************************
to build-in-protected-areas-A3
  scenario_A3_class1_build_in_protected_areas
end

to build-not-in-protected-areas-A3
  scenario_A3_class1
```

```
end

to build-in-not-protected-areas-A3
ifelse Build?-A3
[build-in-protected-areas-A3]
[build-not-in-protected-areas-A3]
end


;; Scenario A3 - Class 2 - non-irrigated arable land

to scenario_A3_class2
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.28 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end

to scenario_A3_class2_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.28 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end

to scenario_A3_class2_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 2]
   and
   random-float 1 < 0.28 ;; Farmers' LUCC intentions
   [
   set modified-landuse  2
   set pcolor 68]
   ]
end


;; Scenario A3 - Class 3 - permanently irrigated land

to scenario_A3_class3
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5]
   [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < -0.17 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
   set pcolor 43]
   ]
end

to scenario_A3_class3_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 4 or modified-landuse = 5  and slope = 0 and slope = 1 and slope = 2]
  [
   if any? patches in-radius 5 with [modified-landuse = 3]
   and
   random-float 1 < -0.17 ;; Farmers' LUCC intentions
   [
   set modified-landuse  3
```

```
    set pcolor 43]
   ]
end

to scenario_A3_class3_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2  or modified-landuse = 4 or modified-landuse = 5 or modified-landuse = 6  and slope = 0 and slope = 1 and slope = 2]
  [
    if any? patches in-radius 5 with [modified-landuse = 3]
    and
    random-float 1 < -0.17 ;; Farmers' LUCC intentions
    [
    set modified-landuse  3
    set pcolor 43]
   ]
end


;; Scenario A3 - Class 4 - permanent crops and heterogeneous agricultural land

to scenario_A3_class4
ask patches with [modified-landuse = 2  or modified-landuse = 3  or modified-landuse = 5]
   [
    if any? patches in-radius 5 with [modified-landuse = 4]
    and
    random-float 1 < -0.01 ;; Farmers' LUCC intentions
    [
    set modified-landuse  4
    set pcolor 32]
   ]
end

to scenario_A3_class4_slope_0_10 ;; Slope for farming : 0-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 and slope = 0 and slope = 1 and slope = 2]
  [
    if any? patches in-radius 5 with [modified-landuse = 4]
    and
    random-float 1 < -0.01 ;; Farmers' LUCC intentions
    [
    set modified-landuse  4
    set pcolor 32]
   ]
end

to scenario_A3_class4_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 5 or modified-landuse = 6 and slope = 0 and slope = 1 and slope = 2]
  [
    if any? patches in-radius 5 with [modified-landuse = 4]
    and
    random-float 1 < -0.01 ;; Farmers' LUCC intentions
    [
    set modified-landuse  4
    set pcolor 32]
   ]
end


;; Scenario A3 - Class 5 - Pastures

to scenario_A3_class5
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4]
  [
    if any? patches in-radius 200 with [modified-landuse = 5]
    and
    random-float 1 < -0.06 ;; Farmers' LUCC intentions
    [
    set modified-landuse  5
    set pcolor 28]
   ]
end
```

```
to scenario_A3_class5_slope_0_10 ;; Slope for farming : 5-10º?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4  and slope = 0 and slope = 1 and slope = 2]
  [
    if any? patches in-radius 200 with [modified-landuse = 5]
    and
    random-float 1 < -0.06 ;; Farmers' LUCC intentions
    [
    set modified-landuse  5
    set pcolor 28]
    ]
end

to scenario_A3_class5_forest_to_agriculture ;; Conversion from Forest to Agriculture?
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 6 and slope = 0 and slope =
1 and slope = 2]
  [
    if any? patches in-radius 200 with [modified-landuse = 5]
    and
    random-float 1 < -0.06 ;; Farmers' LUCC intentions
    [
    set modified-landuse  5
    set pcolor 28]
    ]
end

;; Scenario A3 - Class 6 - Forest and semi-natural areas

to forest-A3-0
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A3-10
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.1 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A3-20
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.2 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A3-30
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.3 ;; Users' LUCC intentions
[
```

```
set modified-landuse  6
set pcolor 72]
]
end

to forest-A3-40
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.4 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to forest-A3-50
ask patches with [modified-landuse = 2 or modified-landuse = 3 or modified-landuse = 4 or modified-landuse = 5]
[
if any? patches in-radius 5 with [modified-landuse = 6]
and
random-float 1 < 0.5 ;; Users' LUCC intentions
[
set modified-landuse  6
set pcolor 72]
]
end

to for0-A3
If ForestA3 = "0%"
[
forest-A3-0
]
end

to for10-A3
If ForestA3 = "10%"
[
forest-A3-10
]
end

to for20-A3
If ForestA3 = "20%"
[
forest-A3-20
]
end

to for30-A3
If ForestA3 = "30%"
[
forest-A3-30
]
end

to for40-A3
If ForestA2 = "40%"
[
forest-A3-40
]
end

to for50-A3
If ForestA3 = "50%"
[
forest-A3-50
]
end
```

```
to f_A3
If ForestA3 = "0%"
[
forest-A3-0
]
If ForestA3 = "10%"
[
forest-A3-10
]
if ForestA3 = "20%"
[
forest-A3-20
]
if ForestA3 = "30%"
[
forest-A3-30
]
if ForestA3 = "40%"
[
forest-A3-40
]
if ForestA3 = "50%"
[
forest-A3-50
]
end

;**********************************************
;   conversion of forest to agriculture?  A3 ;
;**********************************************
to convert-forest-to-agriculture-A3
scenario_A3_class2_forest_to_agriculture
scenario_A3_class3_forest_to_agriculture
scenario_A3_class4_forest_to_agriculture
scenario_A3_class5_forest_to_agriculture
end

to not-convert-forest-to-agriculture-A3
scenario_A3_class2
scenario_A3_class3
scenario_A3_class4
scenario_A3_class5
end

to forest-to-agriculture-A3
 ifelse Forest-A3?
 [convert-forest-to-agriculture-A3]
 [not-convert-forest-to-agriculture-A3]
end


;***********************************
 ;      slope farming 0-10   A3 ;
 ;***********************************
to slope-farming-0-10-yes-A3
scenario_A3_class2_slope_0_10
scenario_A3_class3_slope_0_10
scenario_A3_class4_slope_0_10
scenario_A3_class5_slope_0_10
end

to slope-farming-0-10-no-A3
scenario_A3_class2
scenario_A3_class3
scenario_A3_class4
scenario_A3_class5
end

to slope-farming-0-10-A3
 ifelse A3-0-10º?
 [slope-farming-0-10-yes-A3]
```

```
 [slope-farming-0-10-no-A3]
end


;****************************
;     LEGEND
;****************************
to-report %artificial_surfaces
 report count patches with [modified-landuse = 1] / Count patches * 100
end

to-report %non_irrigated_arable_land
 report count patches with [modified-landuse = 2] / Count patches * 100
end

to-report %permanently_irrigated_land
 report count patches with [modified-landuse = 3] / Count patches * 100
end

to-report %permanent_crops_and_heterogeneous_agricultural_land
 report count patches with [modified-landuse = 4] / Count patches * 100
end

to-report %pastures
 report count patches with [modified-landuse = 5] / Count patches * 100
end

to-report %forest_and_semi_natural_areas
 report count patches with [modified-landuse = 6] / Count patches * 100
end

to-report %water_bodies
 report count patches with [modified-landuse = 7] / Count patches * 100
end

;****************************
;     END
;****************************

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```
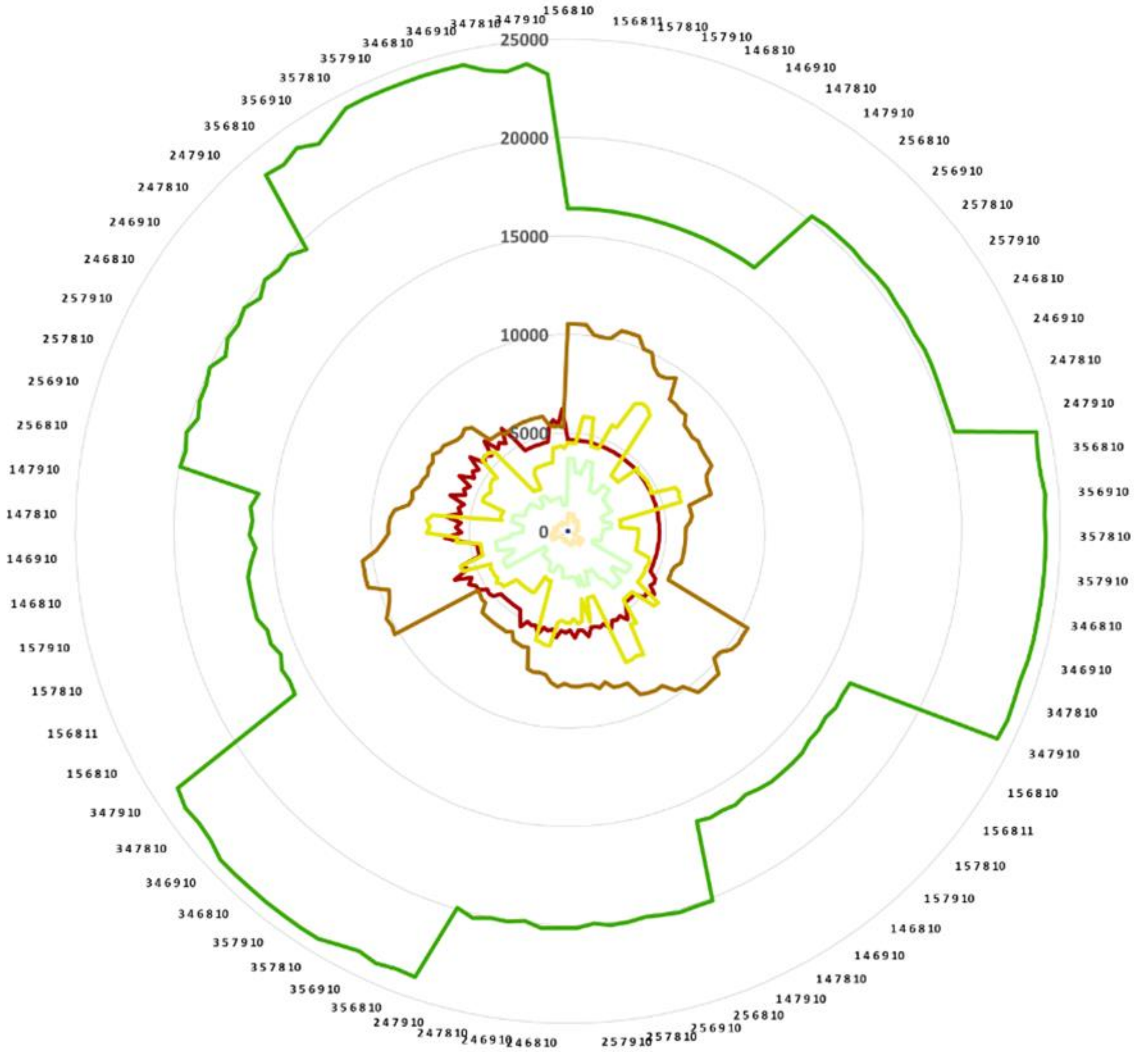
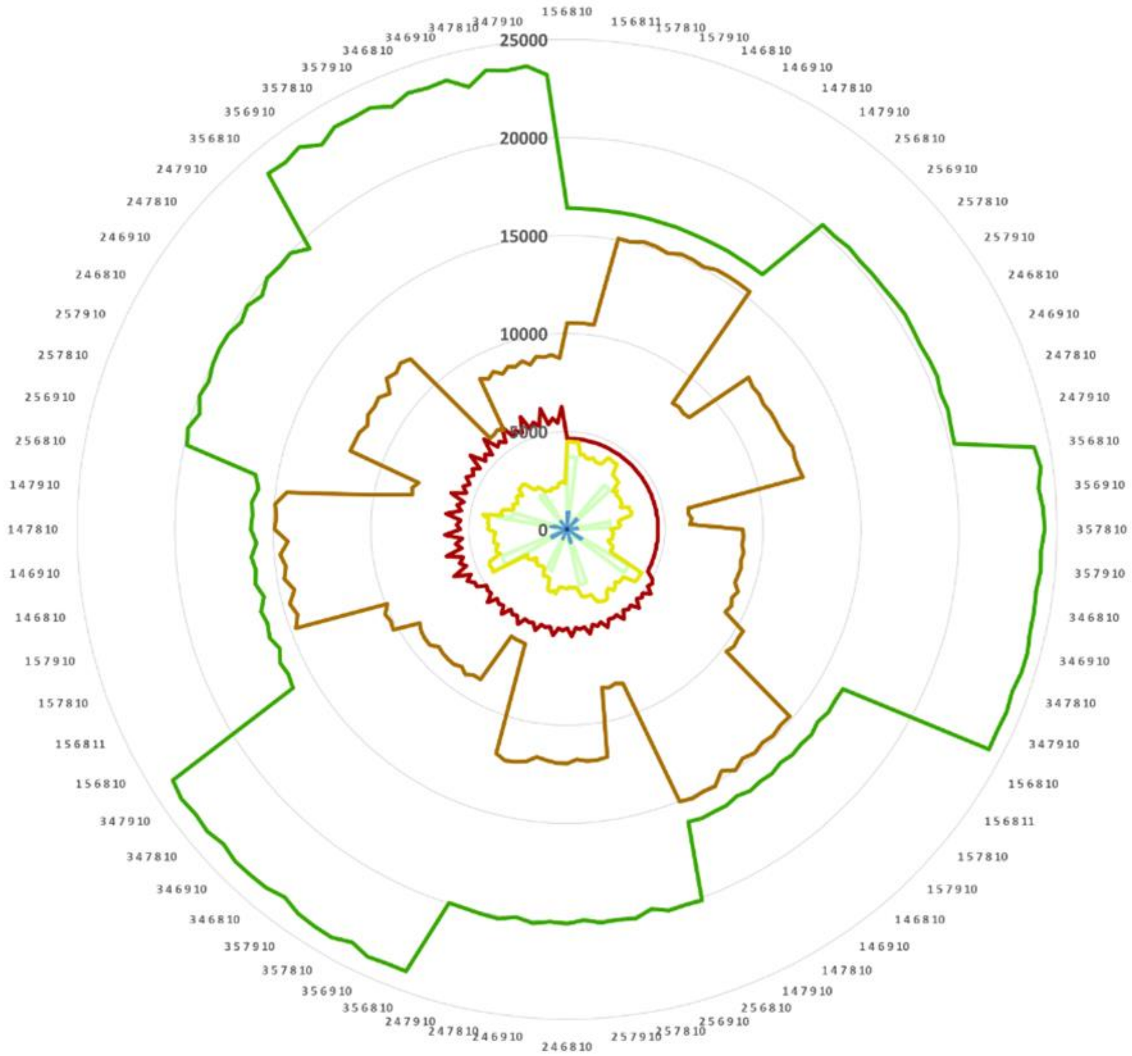

Appendix V

A0 scenario



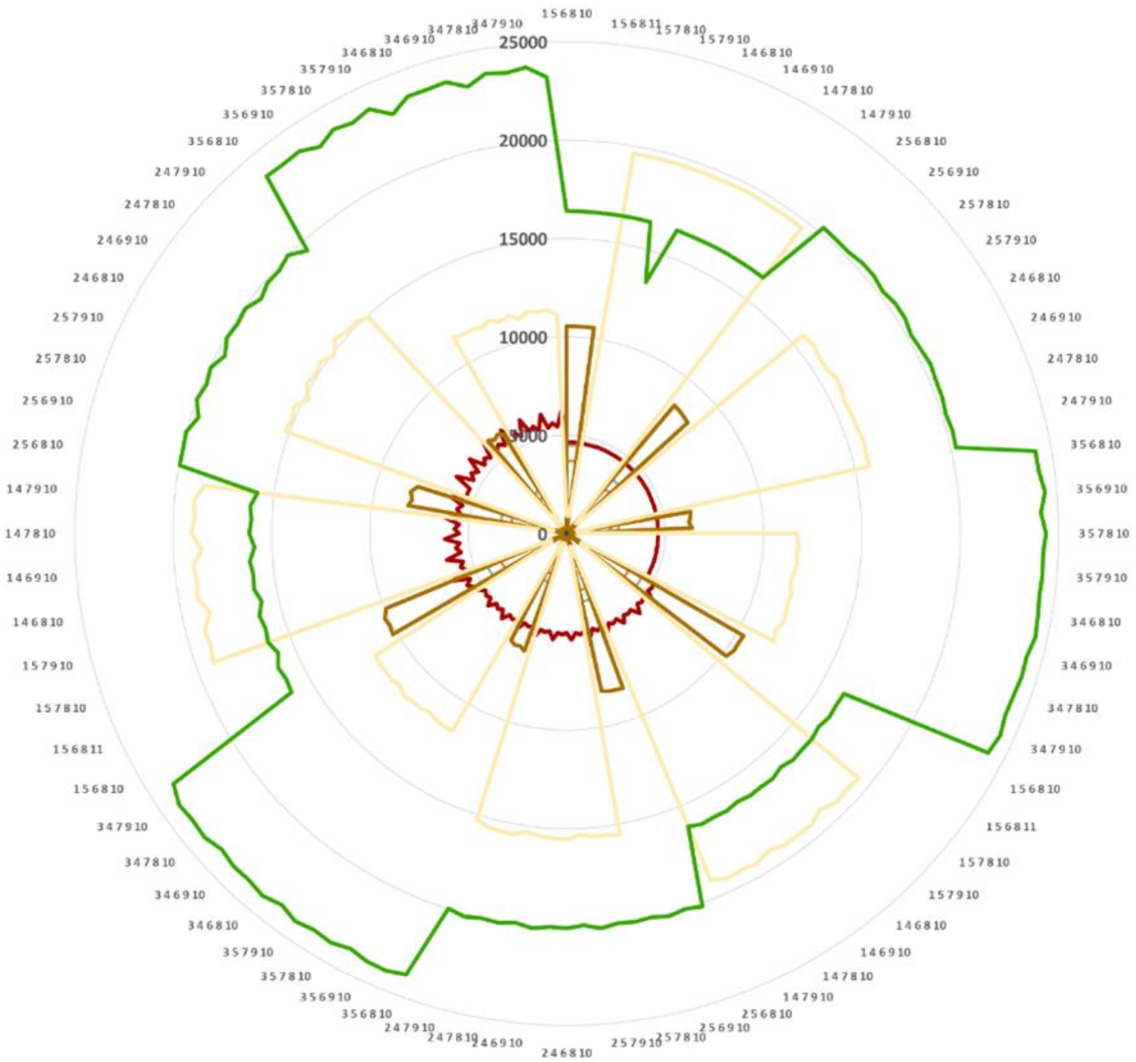
A0 scenario – FARMER model (144 simulations). Code: 1 – forest 0%; 2 - forest 20%; 3 – forest 40%; 4 - convert forest to agriculture (false); 5 – do not convert forest to agriculture (true); 6 – farming 0-10º (true); 7 - farming 0-20º (false); 8 – distance to existence urban areas (100m); 9 – distance to existence urban areas (200m); 10 – distance to road network (100m); 11 – distance to road network (200m).

A1 scenario



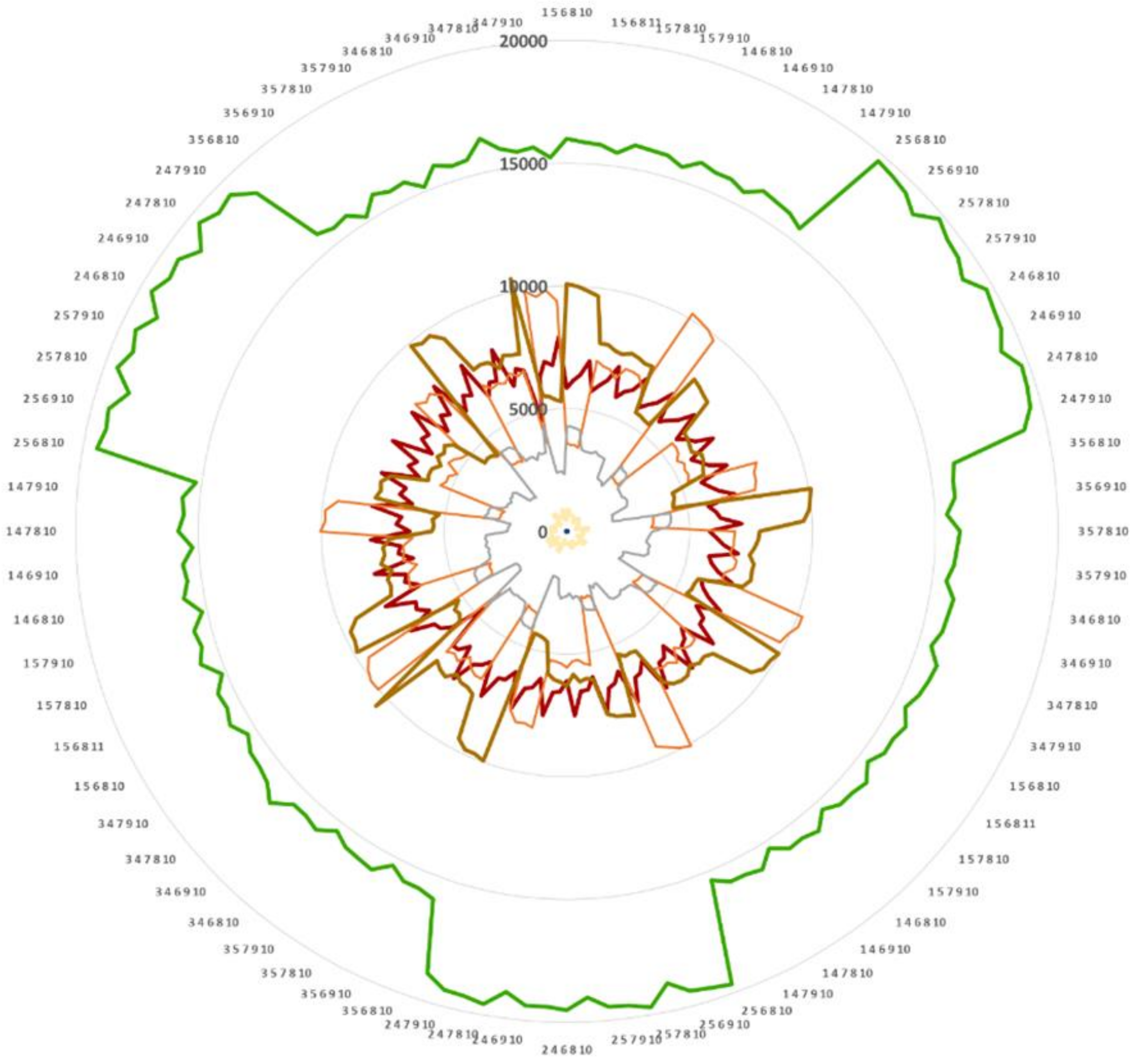
A1 scenario – FARMER model (144 simulations). Code: 1 – forest 0%; 2 - forest 20%; 3 – forest 40%; 4 - convert forest to agriculture (false); 5 – do not convert forest to agriculture (true); 6 – farming 0-10º (true); 7 - farming 0-20º (false); 8 – distance to existence urban areas (100m); 9 – distance to existence urban areas (200m); 10 – distance to road network (100m); 11 – distance to road network (200m).

A2 scenario



A2 scenario – FARMER model (144 simulations). Code: 1 – forest 0%; 2 - forest 20%; 3 – forest 40%; 4 - convert forest to agriculture (false); 5 – do not convert forest to agriculture (true); 6 – farming 0-10º (true); 7 - farming 0-20º (false); 8 – distance to existence urban areas (100m); 9 – distance to existence urban areas (200m); 10 – distance to road network (100m); 11 – distance to road network (200m).

B0 scenario



B0 scenario – FARMER model (144 simulations). Code: 1 – forest 0%; 2 - forest 20%; 3 – forest 40%; 4 - convert forest to agriculture (false); 5 – do not convert forest to agriculture (true); 6 – farming 0-10º (true); 7 - farming 0-20º (false); 8 – distance to existence urban areas (100m); 9 – distance to existence urban areas (200m); 10 – distance to road network (100m); 11 – distance to road network (200m).